รายงานวิจัยฉบับสมบูรณ์

เทคนิคการลดเวลาในการทำงานของเครือข่ายค๊อกนิทีฟ
สำหรับการสื่อสารของระบบสมาร์ทกริด

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สัญญาเลขที่ MRG5680101

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มหาวิทยาลัยเทคโนโลยีพระจอมเกล้าพระนคเหนือ

สนับสนุนโดยสำนักงานคณะกรรมการอุดมศึกษา สำนักงานกองทุนสนับสนุนการวิจัย

และมหาวิทยาลัยเทคโนโลยีพระจอมเกล้าพระนครเหนือ

Abstract

In this research, we propose the novel spectrum sensing techniques for time reduction in cognitive radio (CR) network for smart grid (SG) communication. CR network is received highly consideration to the communications infrastructure for SG because CR has been proposed to solve the spectrum scarcity problem by offering several advantages to utilize spectrum opportunely with dynamic spectrum management techniques. CR network has two important actors: Primary user (PU) and Secondary user (SU). PU is the owner of a licensed channel that has the priority to use the spectrum and SU is the occasional user that is responsible for sensing the licensed spectrum, identifying the unused channels in the absence of PU. CR system has four main functions including spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing. To achieve this requirement, the SU need to have the capability to detect the availability of spectrum bands for possible utilize and aware of the PU reclaim rights of usage which is referred to “spectrum sensing”. Thus, spectrum sensing is the function of cognitive radio that is playing a major role for efficiency spectrum usage.

In this research, we propose four spectrum sensing schemes in CR network for SG communication system. First, we propose fast spectrum sensing with coordinate system (FSC). FSC is knowledge-based spectrum sensing method. This novel technique decomposes a spectrum with high complexity into a new coordinate system and it uses these features in its PU detection process. Not only is the space of a buffer that is used to store information about a PU reduced, but also the sensing process is fast. Second, we propose double constraints adaptive energy detection (DCAED) for spectrum sensing. DCAED is blind spectrum sensing technique. This method adapts the threshold based on 2 accuracy of performance metrics. By using probability of detection and probability of false alarm as the target accuracy performance metrics, DCAED overcomes a demerit of ED in tradeoff between probability of detection and probability of false alarm when the system threshold is set by selecting only probability of detection or probability of false alarm. Third, we proposed two-stage spectrum sensing scheme exploits the merits of ED, MME and CAV techniques to determine the existence of the primary user. The ED performs spectrum sensing within a short time and offers a reliable detection at high SNRs condition. MME and CAV are robust to noise power uncertainty. Due to the combination of these techniques, the proposed schemes offer much more reliable detection when the uncertainty of noise power occurs. Finally, we propose modified- fast spectrum sensing with coordinate system (MFSC), to perform spectrum sensing under path loss effect and noise uncertainty.

Keyword: Cognitive radio, Spectrum sensing, PCA, Noise uncertainty, Path loss effect

บทคัดย่อ

งานวิจัยฉบับนี้ ผู้วิจัยนำเสนอการตรวจจับสเปคตรัมแบบใหม่เพื่อทำการลดเวลาในการทำงานของเครือข่ายค็อกนิทีฟสำหรับการสื่อสารของระบบสมาร์ทกริด ระบบค็อกนิทีฟได้รับความสนใจเป็นอย่างมากในการที่จะนำมาประยุกต์ใช้ในการสื่อสารของระบบสมาร์ทกริด เนื่องจากระบบค็อกนิทีฟเป็นระบบที่สามารถแก้ปัญหาความไม่เพียงพอในการใช้งานสเปคตรัม โดยระบบค็อกนิทีฟจะทำการหาช่วงสเปคตรัมที่ผู้ใช้หลักไม่ได้ใช้งานแล้วนำสเปคตรัมที่ว่างนั้นมาใช้ในการส่งข้อมูลสื่อสาร องค์ประกอบหลักของระบบค็อกนิทีฟประกอบด้วย ผู้ใช้หลักและผู้ใช้รอง ผู้ใช้หลัก คือ ผู้ใช้สเปคตรัมที่ได้รับอนุญาตในการเข้าใช้งาน ส่วนผู้ใช้รอง คือ อุปกรณ์ของระบบค็อกนิทีฟที่เข้าใช้งานสเปคตรัมของผู้ใช้หลักเมื่อสเปคตรัมไม่ได้ถูกใช้งาน ระบบค็อกนิทีฟมีฟังก์ชันการทำงานหลักอยู่ 4 ฟังก์ชันได้แก่ การตรวจจับสเปคตรัม การจัดการสเปคตรัม การย้ายสเปคตรัม และการแบ่งการใช้งานสเปคตรัม โดยเงื่อนไขหลักของระบบค็อกนิทีฟคือ ผู้ใช้รองจะต้องไม่สร้างการรบกวนการใช้งานสเปคตรัมของผู้ใช้หลักอย่างเด็ดขาด ซึ่งฟังก์ชันที่จะป้องกันการรบกวนของผู้ใช้รองต่อผู้ใช้หลัก คือ ฟังก์ชันการตรวจจับสเปคตรัม ดังนั้น ในงานวิจัยฉบับนี้จึงมุ่งเน้นที่จะออกแบบการตรวจจับสเปคตรัมแบบใหม่ที่ใช้เวลาในการทำงานต่ำและมีประสิทธิภาพในการทำงานดีกว่าเทคนิคการตรวจจับเสปคตรัมที่มีอยู่ในปัจจุบัน

ในงานวิจัยฉบับนี้ ผู้วิจัยได้นำเสนอการตรวจจับสเปคตรัมแบบใหม่ทั้งหมด 4 ชนิด โดยแต่ละชนิดมีรายละเอียดดังต่อไปนี้ ชนิดที่ 1 การตรวจจับสเปคตรัมอย่างเร็วโดยการใช้ระบบพิกัด วิธีนี้จะทำการแยกสเปคตรัมของผู้ใช้หลักชนิดต่างๆให้ไปอยู่ในระบบพิกัดแบบใหม่ แล้วนำลักษณะที่อยู่ในพิกัดแบบใหม่นี้ไปทำการตรวจหาการมีหรือไม่มีการใช้งานสเปคตรัมของผู้ใช้หลัก ซึ่งวิธีที่นำเสนอนี้สามารถตรวจสอบการใช้งานสเปคตรัมได้อย่างมีประสิทธิภาพอีกทั้งยังใช้เวลาในการตรวจจับที่เร็วกว่าวิธีเดิมๆ อีกด้วย ชนิดที่ 2 การตรวจจับพลังงานแบบปรับค่าเงื่อนไข 2 ค่า วิธีนี้เป็นการตรวจจับแบบบอด คือ ไม่จำเป็นต้องทราบข้อมูลของผู้ใช้หลักในการตรวจสอบการใช้งาน ทำให้ความซับซ้อนของการตรวจจับมีค่าต่ำ ชนิดที่ 3 การตรวจจับสเปคตรัมแบบสองขั้นตอน วิธีนี้จะทำการรวมข้อดีของการตรวจจับแบบ ED, MED และ CAV เข้าไว้ด้วยกัน จากผลการทดลองพบว่า การตรวจจับวิธีนี้มีประสิทธิภาพสูงกว่าการตรวจจับแบบ 1 ขั้นตอนปกติ อีกทั้งยังสามารถใช้งานในสภาพแวดล้อมที่มีภาวะสัญญาณรบกวนแบบไม่คงที่ได้อีกด้วย ชนิดสุดท้าย คือ การปรับปรุงการตรวจจับชนิดที่ 1 โดยทำการปรับปรุงค่าตัวแปรบางค่า เพื่อที่จะให้การตรวจจับชนิดนี้สามารถใช้งานในสภาพแวดล้อมที่มีสัญญาณรบกวนแบบไม่คงที่และสัญญาณที่เครื่องรับยังได้รับผลกระทบจากการสูญเสียค่าพลังงานตามระยะทางอีกด้วย

คำสำคัญ: ระบบค็อกนิทีฟ, การตรวจจับสเปคตรัม, พีซีเอ, สัญญาณรบกวนแบบไม่คงที่, ผลกระทบจากการสูญเสียค่าพลังงานตามระยะทาง

Executive Summary

1) ความสำคัญและที่มาของปัญหา

In general, the traditional power grids are used to carry power from a few central generators to a large number of users or customers. In contrast, Smart grid (SG) uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network. SG is the integration of secure, high-speed and reliable data communication networks to manage the complex power systems intelligently and effectively. Thus, SG has harsh and complex environmental conditions, connectivity problems, dynamic topology changes, and interference and fading issues during wireless communication. It is difficult to design the information and communication technologies (ICTs) system for the overall power grid. Thus, the choice of communication infrastructure for SG is highly critical to provide reliable, secure, and efficient data delivery between SG components. For solving these problems, Cognitive radio (CR) networks can be benefited to address the unique challenges of SG, such as multipath fading, reliability and delay requirements, different spectrum characteristics changing over location and time, noise, and harsh environmental conditions.

Cognitive radio (CR) network is proposed for overcome the "Spectrum crisis" problem by offering several advantages to utilize spectrum opportunistically with dynamic spectrum management techniques. CR network has two important actors: 1) primary user (PU) and 2) secondary user (SU). PU is the owner of a licensed channel that has the priority to user the spectrum. SU is the occasional user that is responsible for sensing the licensed spectrum, identifying the unused channels in the absence of PU and a SU is called a CR user. CR system has four main functions including spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing. The spectrum sensing detects unused spectrum and sharing the spectrum without harmful interference with other users. The spectrum management captures the best available spectrum to meet user communication requirements. The spectrum mobility maintains seamless communication requirements during the transition to better spectrum. The spectrum sharing provides the fair spectrum scheduling method among coexisting other uses. Due to the legacy rights in spectrum band of PU, the SU must vacate the band whenever the PU need to reclaim the spectrum usage rights. To achieve this requirement, the SU need to have the capability to detect the availability of spectrum bands for possible utilize and aware of the PU reclaim rights of usage which is referred to "spectrum sensing". Thus, spectrum sensing is the function of cognitive radio that is playing a major role for efficiency spectrum usage.

In this research, we propose four spectrum sensing schemes in CR network for SG communication system. First, we propose fast spectrum sensing with coordinate system (FSC). FSC is knowledge-based spectrum sensing method. This novel technique decomposes a spectrum with high complexity into a new coordinate system of salient features and it uses these features in its PU detection process. Not only is the space of a buffer that is used to store information about a PU reduced, but also the sensing process is fast. Second, we propose double constraints adaptive energy detection (DCAED) for spectrum sensing. DCAED is blind spectrum sensing technique. This method adapts the threshold based on 2 accuracy of performance metrics. By using probability of detection and probability of false alarm as the target accuracy performance metrics, DCAED overcomes a demerit of ED in tradeoff between probability of detection and probability of false alarm when the system threshold is set by selecting only probability of detection or probability of false alarm. Third, we proposed two-stage spectrum sensing scheme exploits the merits of ED, MME and CAV techniques to determine the existence of the primary user. The ED performs spectrum sensing within a short time and offers a reliable detection at high SNRs condition. MME and CAV are robust to noise power uncertainty. Due to the combination of these techniques, the proposed schemes offer much more reliable detection when the uncertainty of noise power occurs. Finally, we propose modified- fast spectrum sensing with coordinate system (MFSC), to perform spectrum sensing under path loss effect and noise uncertainty.

2) วัตถุประสงค์

This project proposes the novel spectrum sensing techniques in CR network for SG communication. The proposed techniques have a minimum time requirement and give a better performance than the conventional spectrum sensing methods. Moreover, we consider two channel environments including AWGN channel and the channel that consider the noise uncertainty and path loss effect.

3) ระเบียบวิธีวิจัย

1. Literature review of the spectrum sensing algorithms of cognitive radio (CR) networks: Study research papers relevant to the research works of the research.
    - 1.1 Study research papers relevant to spectrum sensing algorithms.
    - 1.2 Study research papers concerning with improving the spectrum sensing algorithms.
    - 1.3 Study research papers regarding the time requirement of the spectrum sensing algorithms.
2. Simulation software implementation of the spectrum sensing algorithms

2.1 Consider and compare the time requirement of each of spectrum sensing techniques from literature reviews.

2.2 Provide time delay mathematical model of the spectrum sensing algorithm for CR network.

2.2 Develop the time reduction of the spectrum sensing algorithm for CR network.

3. Simulation software implementation of the proposed technique

3.1 Develop the proposed technique for the spectrum sensing algorithm simulation program.

3.2 Test the time requirement of the proposed spectrum sensing algorithm for CR network.

4. Project summary

4.1 Summarize the major finding as we found in step 3 and conclude the performance of the proposed time reduction in all concerned aspects.

4.2 Check whether the conclusions meet all the objectives of the research work of the research.

4.3 Write the research report.

4) แผนการดำเนินงานวิจัยตลอดโครงการในแต่ละช่วง 6 เดือน

1st year of the project

Months 1-3	Literature review of Spectrum sensing algorithm of Cognitive radio networks.
Months 4-6	Improved observation model for spectrum sensing algorithm.
Months 7-10	Simulation software implementation of improved observation model.
Months 11-12	Literature review of communication protocol for smart grid.

2nd year of the project

Months 13-15	Improved observation model for spectrum sensing algorithm that can be used under noise uncertainty and path loss effect.
Months 16-18	Simulation software implementation of improved observation model.
Months 19-21	Evaluation of developed model and algorithm and write the journal.
Months 22-24	Project summary.

Chapter 1

Introduction

1.1 Introduction to the research problem and its significance

In general, the traditional power grids are used to carry power from a few central generators to a large number of users or customers. In contrast, Smart grid (SG) uses two-way flows of electricity and information to create an automated and distributed advanced energy delivery network. SG is the next-generation of electric power system since 2005. Therefore, SG becomes one of the fast growing research topics [1-11] because this system is a promising solution for energy crisis. In [1], J. Ekanayake, et al. present the six major advantages of SG such as SG can manage demand response and demand side through the integration of SG devices and SG can provide information related to energy use and price to customers. One of the important features of SG is the integration of secure, high-speed and reliable data communication networks to manage the complex power systems intelligently and effectively. Thus, SG has harsh and complex environmental conditions, connectivity problems, dynamic topology changes, and interference and fading issues during wireless communication. It is difficult to design the information and communication technologies (ICTs) system for the overall power grid. Thus, the choice of communication infrastructure for SG is highly critical to provide reliable, secure, and efficient data delivery between SG components.

The communication infrastructure between energy generation, transmission, and distribution and consumption needs two-way communications, interoperability between advanced applications and end-to-end secure and reliable communications with sufficient bandwidth and low-latencies [2-11]. The important communication and networking technologies which may be applicable in future SG. Six important communication types [2] include wireless mesh network, such as WiMAX, cellular communication system, such as GSM, WCDMA, and CDMA-2000, wireless communications based on 802.15.4, such as ZigBee, WirelessHART, and ISA100.11a, microwave or free-space optical communications, fiber-optic communications and power line communication (PLC). The first four communication technologies are the wireless communication and the last two technologies are the wired communication. The compare the performance between wireless technologies and wired technologies for SG are considered in [3]. They can conclude that the wireless communication technologies have significant benefits more than wired technologies because the wireless communication has low installation cost, rapid deployment, mobility, and more suitable for remote end applications. In [4-5], they study the performance of the current communication technologies that are applied to SG. They found that the current communication capabilities of the existing power systems are limited to small-scale local regions and these methods implement basic functionalities for system monitoring and control which do not yet meet the demanding communication requirements for the automated and intelligent management in the next-generation electric power systems. Therefore, a key point in the success of SG technology is how to meet the complicated requirement in the communication. It demands high communication quality and energy efficiency while taking care of the system expenses and bandwidth. The bandwidth is needed to manage, store and integrate the large amounts of data that smart devices will produce. For solving these problems, Cognitive radio (CR) networks can be benefited to address the unique challenges of SG, such as multipath fading, reliability and delay requirements, different spectrum characteristics changing over location and time, noise, and harsh environmental conditions.

Many works in literature proposed shown that CR network appropriates to SG communication [12-28]. These works also present the research challenges of CR network for SG communication that can be summarized as shown below:

- Quality of Service (QoS)

CR network for SG applications have different QoS requirements including reliability, latency, and data rate. Additionally, SG is a heterogeneous network and it contains electric equipment which has dramatically different limitations, such as storage capability and computing power. Hence, it is still an open research issue to design QoS-aware communication protocols capable way.

- Interoperability

SG needs advanced communication protocols among each of its component to exchange information independent from manufacture or any type of physical device. Thus, different communication technologies and several standards will be used to proper the specific QoS requirements of SG components and applications. These communication technologies may demand operating on different spectrum bands.

- Interference

Interference avoidance scheme should be applied to the CR networks under SG environments. The spectrum management cycle can exclude this problem by providing spectrum sharing functionality.

- Dynamic Spectrum Usage

After the selection of the best available channel for the required SG application, the next step is to make the network protocols adaptive to the chosen spectrum.

Cognitive radio (CR) Network is proposed for overcome the “Spectrum crisis” problem by offering several advantages to utilize spectrum opportunistically with dynamic spectrum management techniques [29-35]. CR network has two important actors: 1) primary user (PU) and 2) secondary user (SU). PU is the owner of a licensed channel that has the priority to user the spectrum. SU is the occasional user that is responsible for sensing the licensed spectrum, identifying the unused channels in the absence of PU and a SU is called a CR user. In [29-30], an introduction of the CR technology and its network architecture are provided. They define the main functions for CR into four topics including spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing. The spectrum sensing detects unused spectrum and sharing the spectrum without harmful interference with other users. The spectrum management captures the best available spectrum to meet user communication requirements. The spectrum mobility maintains seamless communication requirements during the transition to better spectrum. The spectrum sharing provides the fair spectrum scheduling method among coexisting other uses.

Spectrum sensing is an important to play a role in CR network to efficiently and accurately detect primary user for avoiding interference to primary user [36-42]. The requirement for real-time processing indeed poses challenges on implementing spectrum sensing algorithms. Trade-off between the complexity and the effectiveness of spectrum sensing algorithms should be taken into consideration. Therefore, in this research, we will propose the new spectrum sensing schemes that has the minimum time requirement and gives the good performance.

1.2 Literature review

In this research, we propose the new spectrum sensing techniques in CR network for SG communication. The proposed techniques can classify into two types of channel environment. First, we present two spectrum sensing methods under AWGN channel. Second, we propose two spectrum sensing techniques under noise uncertainty and path loss effect. Therefore, in this section, we will review the relevant research papers, published in the conferences and journals, which cover spectrum sensing techniques of both environments.

In this part, we will review the literatures about CR network for SG communication [12-28]. In [12], they provide an overview at the current communication technologies for SG, and discuss the still-open research issues in this field. Furthermore, they review the CR network based SG communication for solving the resources scarcity crisis problem. In [13], they present a comprehensive review about SG characteristics and CR-based SG applications. They also discuss architectures to support CR networks in SG applications, major challenges, and open issues. Four major challenges that are considered include Quality of Service (QoS), Interoperability, Interference, and Dynamic spectrum usage. In [14], they compare SG with communication systems in general and with CR. Their simulation results confirm that CR technique is a solution for the problem of spectrum scarcity. In [15], they propose the application of CR based on the IEEE 802.22 standard in SG wide area networks (WANs). The proposed method can work as a secondary radio particularly: urban and rural. In urban area, the proposed scheme is a backup in disaster management. On the other hand, a stand-alone radio based on IEEE 802.22 can effectively provide broadband access for rural area. In [16-17], they present an unprecedented CR based communications architecture for SG, which is mainly motivated by the explosive data volume, diverse data traffic, and need for QoS support. The proposed architecture is decomposed into three subareas: cognitive home area networks (CogHANs), cognitive neighborhood area networks (CogNANs), and cognitive wide area networks (CogWANs), depending on the service ranges and potential applications. Finally, they focus on dynamic spectrum access and sharing in each subarea.

When we combine CR network and SG system together, the most of researches propose techniques for solving spectrum management functionality in CR network for improving the performance of CR network for SG communication. The spectrum management functionality can be classified into four processes: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. In [18-20], they propose dimensionality reduction techniques such as principal component analysis (PCA), kernel PCA, and landmark maximum variance unfolding (LMVU) for spectrum sensing context on Wi-Fi signal measurements. Moreover, they provide the compressed sensing algorithms such as Bayesian compressed sensing and the compressed sensing Kalman filter for recovering the sparse smart meter transmissions. In [21], they propose parallel processing techniques based on graphics processing unit (GPU) for accelerate processing of spectrum sensing and dynamic access. In [22], they focus on the spectrum resource management in CogNANs for efficient SG services. They propose a new spectrum access paradigm called hybrid spectrum access, in which both licensed and unlicensed spectrum bands are intelligently scheduled for the transmission of SG services. Numeric results indicate that the proposed technique strategy significantly improves the network capacity in supporting the SG services, compared to the traditional fixed spectrum access strategy. In [23], they propose spectrum-aware and cognitive sensor networks to overcome spatio-temporally varying spectrum characteristics and harsh environmental conditions for wireless sensor networks (WSN)-based SG applications. Specially, potential advantages, application areas, and protocol design principles of spectrum-aware and cognitive sensor networks (SCSN) are introduced. A case study is also presented to reveal the reliable transport performance in SCSNs for different smart grid environments. The goal of A. O. Bicen, et al. is to envision potentials of SCSNs for reliable and low-cost remote monitoring solutions for smart grid.

On the other hand, the time requirement problem is the one of fundamental problems for data communication [24-28]. In [24], they consider the current communication technologies for SG. Their knowledge can conclude that the current communication techniques are not support for the real time communication of SG. Moreover, In [25], they confirm that SG requires the critical real-time systems. For CR network for SG communication, several works have studied the optimization of sensing time to tradeoff between interference avoidance and sensing efficiency [26-27], since spectrum sensing and data transmission cannot be performed at the same time. In [28], they introduce spectrum sensing and channel switching techniques of CR into SG communication. They find optimal sensing time to reduce packet loss rate and delay, under the constraint that the PU is sufficiently protected. They formulate the sensing-delay tradeoff problem and prove that it has unique optimal sensing time which yields the minimum delay. However, this paper did not compare the proposed technique with the conventional techniques. Additionally, they also consider in only CogHANs network architecture. Therefore, CR network for SG communication needs a novel spectrum sensing technique that has a minimum time requirement and gives a good performance when compare with other techniques.

In this research, we will propose a new spectrum sensing that has a minimum time requirement and gives the good performance. Hence, in this part, we will review the literatures about the spectrum sensing in CR network.

Three parameters are defined to evaluate the efficiency of spectrum sensing — accuracy of detection, computational complexity, and sensing time. The accuracy of detection is defined by the rate of correct detection of PUs when such users are actually present and occupying the spectrums concerned. This is a prime concern of spectrum sensing because a PU must not be affected by an SU. On the other hand, detecting the presence of a PU when in fact the PU is absent, otherwise known as false detection, has to be minimized to fully utilize spectrum bands. The accuracy of detection is usually shown in terms of a statistic; that is, in terms of a probability, which is often referred to as the probability of detection (P_d). Likewise, false detection is sometimes referred to as the probability of false alarm (P_{fa}). In terms of the probability of detection, the higher the probability, the less likely it is that a PU will experience interference.

The second quality of service (QoS) parameter, computational complexity, is described by the computational burden. The complexity of a spectrum sensing technique affects both the amount of energy consumed by the technique during sensing and the latency of the technique. The higher the complexity, the higher the amount of energy consumed and the higher the latency, neither of which is desired. It generally comes at a cost when the spectrum sensing technique needs to improve its accuracy of detection.

The third QoS is sensing time, which is highly related to computational complexity. It should be noted that the computational complexity of a spectrum sensing technique can also be described by sensing time, since this is increased when the computational burden is increased. From the perspective of sensing time, the more channels an SU monitors, the more opportunities they will have of accessing a licensed band. In addition, an increase in sensing time will result in a decrease in an SU's throughput. It is stated in the IEEE 802.22 standard [43] that an SU needs to perform spectrum sensing within 2 s of a set sensing period with a false alarm probability of less than 0.1 and a detection probability higher than 0.9.

Generally, spectrum sensing techniques [44-58] can be classified into the following two groups: blind techniques and techniques based on prior knowledge of a signal. Blind techniques — energy detection (ED) [43-49], maximum eigenvalue detection (MED) [50], covariance absolute value (CAV) [50-52], and maximum to minimum eigenvalue (MME) detection [53-56] — determine the presence of PUs by measuring the energy or correlation of a received signal. Knowledge-based spectrum sensing techniques — matched filter detection (MFD) [43-47], cyclostationary detection (CFD) and leading eigenvector detection (LED) [58] — require information on the patterns of signals from PUs to analyze observed signals. In general, knowledge-based techniques perform with higher accuracy than blind techniques. However, their computational burden and sensitivity to prior information are also higher than blind techniques such as MFD has to know an exactly waveform pattern of primary user signal while CFD needs to know cyclic frequency of primary signal. Furthermore, the performance of knowledge-based techniques are dependent upon on databases of patterns of PU signals; the pattern of a wireless microphone (WM) signal changes from one pattern to another in reality, even though it operates at the same frequency. The IEEE 802.22 standard categorized WM signals into three patterns — silent, soft speaker, and loud speaker [59]. If a new pattern belonging to a WM signal, one not yet in the database, is observed, then the accuracy of the knowledge-based techniques performances will drop. To keep track of all the possible patterns, large-sized databases are required, which in turn, would require the use of large memory spaces. It is factors such as these that will eventually result in a high computational time.

ED [60-63] is the most widely utilized because it consumes the shortest sensing time with the least complexity. However, the accuracy of detection of ED is unreliable under bad condition of communication channel or at low signal to noise ratio (SNR) condition. In [64-65], the performance of ED is improved by using an adaptive threshold. In general, the threshold of ED is set by fixing target performance metrics. There are 2 ways to set a threshold for ED. The first way is done by fixing target probability of false alarm which is called "constant false alarm rate (CFAR)". The other way is done by fixing target probability of detection which is called "constant detection rate (CDR)". An adaptive threshold energy detection (ATED) changes its decision threshold depending on the condition of communication channel. The system threshold switches between the threshold of CFAR and CDR. Although the detection performance of ED is improved, the false alarm detection rate does not achieve the target performance stated by IEEE 802.22 standard which the spectrum sensing technique has to perform spectrum sensing with probability of false detection less than 0.1.

In this paper, we propose double constraints adaptive energy detection (DCAED), a novel adaptive scheme that adapts the threshold controlled by 2 target detection performance including probability detection and probability of false alarm. Since there is no directly way to set the threshold by fixing 2 target performance metrics. There is a parameter that can be set by fixing 2 target performance metrics. This parameter known as "critical sample ($\mathrm{N_c}$)". DCAED exploits a relation between critical sample and two target performance metrics to set an adaptive factor. The adaptive factor is used to change the threshold of DCAED. The simulation results prove that DCAED gives good detection performance in both performance metrics even at low SNRs. In addition, an average sensing time of DCAED also achieves the requirement of IEEE 802.22 standard which is lower than 2 seconds.

On the other hand, we known that the knowledge-based techniques perform with higher accuracy than blind techniques. Therefore, we propose fast spectrum sensing with coordinate system (FSC) that is a knowledge-based technique, whereby the information of a PU is a prerequisite. The main difference from MFD, CFD and LED is that only significant features of original signals are used to construct a coordinate system. While these features reveal the intrinsic patterns of a PU, their dimension is much smaller than the original signal. To construct the new coordinate system, a feature-extraction process and feature-selection processes of a principal component analysis (PCA) [66-67] algorithm are adopted. To determine the existence of a PU, the FSC algorithm measures the percentage (weight) of correspondence between the received signal and a coordinate system. The magnitude of this weight will rise when a PU exists. Alternatively, it will fall when a PU does not exist. The FSC algorithm consumes little memory, requires little computational burden, and has a short sensing time.

The two proposed techniques that are previously descripted are considered in only additive white Gaussian noise (AWGN) channel. However, there are many factors that degrade the performance of the spectrum sensing technique [56] such as low signal-to-noise ratio (SNR) condition, environment of noise uncertainty, fading and shadowing. Therefore, in this paper, we focus on two main factors, including low SNR condition and environment of noise uncertainty. Low SNR condition refers to the condition that power of noise is much more than power of real signal. This condition effects to the decision making of the existence of primary user and may cause harmful interference to primary user. On the contrary, an environment as noise uncertainty always presents in practical. The uncertainty of noise power is caused by transmission of other users. When the uncertainty of noise occurs, there will be a difference in an estimated noise power and real noise power that cause the performance of spectrum sensing technique significantly degrades.

The third proposed technique that considers the noise uncertainty is two-stage spectrum sensing. Since no single-stage spectrum sensing technique is perfect enough to be implemented in CR device, two-stage spectrum sensing technique is proposed. The two-stage spectrum sensing technique improves the performance of conventional spectrum sensing techniques by exploiting individual advantages of conventional spectrum sensing techniques. The framework of the two-stage spectrum sensing technique can be separated into 2 stages including coarse sensing stage (or first stage) and fine sensing stage (or second stage). For a given channel, the existence of primary user is firstly determined by the coarse sensing stage, if the decision value of the first stage is greater than the threshold of the first stage then the spectrum band is declared to be existed. If the decision value of the first stage is lower than the threshold of the first stage, the second stage is activated.

There are two existing two-stage spectrum sensing techniques including energy detection (ED) to cyclostationary detector (CS) two-stage spectrum sensing technique [68-69] and energy detection (ED) to maximum eigenvalue detection (MED) two-stage spectrum sensing technique [70-72]. Mostly, ED [50] is utilized as a first stage of two-stage spectrum sensing technique because it uses less sensing time than the other techniques. For the second stage, there are two types of conventional spectrum sensing techniques that were proposed for this stage such as CS and MED [51, 73]. CS technique offers a reliable performance of detection at low SNRs. However, the CS technique is cannot be used when the cyclic frequency of primary signal is unknown. On the other hand, under the combination of ED and

MED algorithms, the two-stage spectrum sensing technique offers reliable detection at low SNRs and uses short sensing time at high SNRs. The second stage of ED to MED two-stage spectrum sensing technique offers a reliable detection when the noise power is exactly known. However, an environment as noise power uncertainty always presents in practical which makes the detection performance of MED technique significantly degrades.

In this paper, we propose two novel schemes of two-stage spectrum sensing technique for CR, i.e., ED to CAV (covariance absolute value detection) two stage spectrum sensing technique and ED to MME (maximum-minimum eigenvalue detection) two stage spectrum sensing technique. ED is used as the first stage of the proposed algorithms because it performs spectrum sensing within short sensing time and gives reliable detection at high SNR environment. In the second stage, we exploit two difference type of blind detection techniques, including CAV [52-54, 74] and MME [55]. The merit of blind detection technique is that it is robust to the uncertainty of noise power. Under the combination of ED and blind detection techniques, our algorithms offer better detection performance than the existing two-stage spectrum sensing techniques. The simulation results proved that ED to CAV two stage spectrum sensing technique gives the best performance among the others. The performance of spectrum sensing techniques are evaluated through three standard patterns of wireless microphone signal, including, including silent, soft speaker and loud speaker, based on IEEE802.22 document [59]. In our simulation, the patterns of received signal changes randomly.

Finally, we propose modified FSC that re-derives some parameters of FSC algorithm in order to perform spectrum sensing under path loss effect and noise uncertainty since a conventional FSC did not take these factors into the account therefore it is not appropriate to perform spectrum sensing under path loss effect and noise uncertainty. This is due to the fact that the FSC threshold is very sensitive to the strength of signal's power since it performs spectrum sensing under a framework of pattern recognition. Therefore, the FSC threshold is needed to re-derived and vary on the changing in the strength of path loss. In simulation results, we evaluate the performance of MFD, LED and MFSC under path loss effect and take a noise uncertainty into the account in order to make the environment of the communication channel nearly to the practical communication system. From the evaluation, we found that MFD still gives the highest P_{d} when noise uncertainty does not exist. On the other hand, the effect of noise uncertainty does not cause any degradation to the detection performance of LED, while the detection performance of MFD degrades significantly. MFSC algorithm is the most achievable of spectrum sensing requirement when it gives high detection performance while consumes the least average sensing time under noise uncertainty with path loss effect.

1.3 Objectives

This project proposes the novel spectrum sensing techniques in CR network for SG communication. The proposed techniques have a minimum time requirement and give a better performance than the conventional spectrum sensing methods. Moreover, we consider two channel environments including AWGN channel and the channel that consider the noise uncertainty and path loss effect.

1.4 Methodology

1. Literature review of the spectrum sensing algorithms of cognitive radio (CR) networks: Study research papers relevant to the research works of the research.

   1.1 Study research papers relevant to spectrum sensing algorithms.

   1.2 Study research papers concerning with improving the spectrum sensing algorithms.

   1.3 Study research papers regarding the time requirement of the spectrum sensing algorithms.

2. Simulation software implementation of the spectrum sensing algorithms

   2.1 Consider and compare the time requirement of each of spectrum sensing techniques from literature reviews.

   2.2 Provide time delay mathematical model of the spectrum sensing algorithm for CR network.

   2.2 Develop the time reduction of the spectrum sensing algorithm for CR network.

3. Simulation software implementation of the proposed technique

   3.1 Develop the proposed technique for the spectrum sensing algorithm simulation program.

   3.2 Test the time requirement of the proposed spectrum sensing algorithm for CR network.

4. Project summary

   4.1 Summarize the major finding as we found in step 3 and conclude the performance of the proposed time reduction in all concerned aspects.

4.2 Check whether the conclusions meet all the objectives of the research work of the research.

4.3 Write the research report.

1.5 Scope of research

The research problem is the time reduction of CR network for SG communication. The scope of these researches is as follows:

- Study the performance and the limitation of spectrum sensing in the CR network.
- Study the factors that degrade the performance of the spectrum sensing technique.
- Simulate and compare the time requirement communication of the conventional spectrum sensing techniques in the CR network.
- Propose the new spectrum sensing techniques that has lower time requirement and good performance in the CR network.
- Simulate and compare the time requirement communication of the proposed technique in the CR network.

1.6 Schedule for the entire project and expected outputs

1st year of the project

Months 1-3	Literature review of Spectrum sensing algorithm of Cognitive radio networks.
Months 4-6	Improved observation model for spectrum sensing algorithm.
Months 7-10	Simulation software implementation of improved observation model.
Months 11-12	Literature review of communication protocol for smart grid.

2nd year of the project

Months 13-15	Improved observation model for spectrum sensing algorithm that can be used under noise uncertainty and path loss effect.
Months 16-18	Simulation software implementation of improved observation model.
Months 19-21	Evaluation of developed model and algorithm and write the journal.
Months 22-24	Project summary.

Chapter 2
Basic Concept

This chapter gives a brief introduction to wireless microphone signals based on the IEEE 802.22 standard and conventional spectrum sensing techniques. After that, two factors that degrade the performance of spectrum sensing techniques, i.e., noise uncertainty and path loss, are briefly reviewed.

2.1 Wireless microphone signals

In this research, a wireless microphone (WM) signal is considered as a PU signal. To evaluate the performance of spectrum sensing techniques for WM signal, the WM signal is modeled by IEEE 802.22 [59]. Therefore, the WM signal is categorized into 3 models — silent, soft speaker and loud speaker. Silent means that the PU transmits only the frequency modulation (FM) carrier and tone key. Soft speaker means that the PU transmits the FM carrier with some moderate amount of deviation. Loud speaker means that the PU transmits the FM carrier with near the maximum amount of deviation.

The WM signal can be expressed as

$$s(t) = A_{\mathrm{c}}\cos(2\pi f_{\mathrm{c}}t + 2\pi k_{\mathrm{f}}\int_0^t m(\tau)\mathrm{d}\tau), \tag{2-1}$$

$$m(\tau) = \sin(f_{\mathrm{m}}t), \tag{2-2}$$

where A_{c} is amplitude of carrier signal, $m(\tau)$ is the modulating signal, f_{m} is message frequency, f_{c} is carrier frequency and k_{f} is frequency modulation (FM) deviation factor.

Based on IEEE 802.22, the parameter of silent, soft speaker and loud speaker of the WM signal are set as shown in Table 2-1.

Table 2-1. Model of wireless microphone signal [59].

	Silent	Soft speaker	Loud speaker
$m(\tau)$ frequency (kHz)	32	3.9	13.4
FM deviation factor (kHz) (k_{f})	±5	±15	±32.6

Figure 2-1 modulation of wireless microphone signals at silent situation, soft speaker situation and loud speaker situation, respectively.

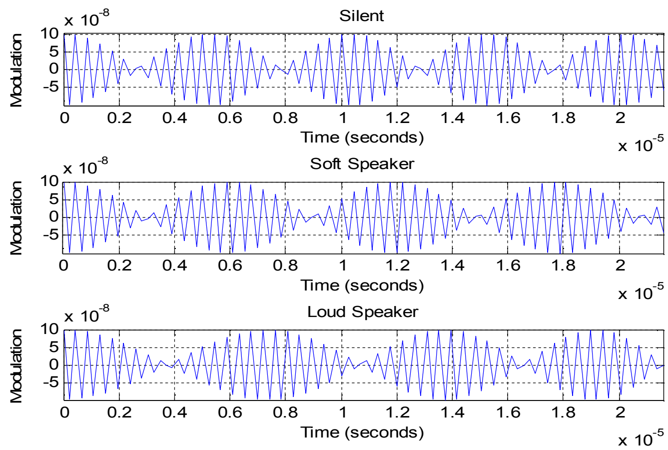


Figure 2-1 Three models of wireless microphone signal

2.2 Spectrum Sensing Techniques

Spectrum sensing is a critical function of CR that periodically detects the existence of a PU during its sensing period. Generally, spectrum sensing techniques can be broadly classified into two types: 1) detection techniques based on prior knowledge about signal, 2) blind detection techniques which do not require any prior knowledge. The detection technique based on prior knowledge requires for the information of primary signal's pattern. This sensing technique normally offers better sensing performance than blind detection technique. Nevertheless, when the secondary user does not have the information about the pattern of PU, the sensing performance of this technique is also drop. The solution of this problem is that the secondary user has to keep various signals' pattern of PU in the database which makes the system requires large size of memory. In addition, the increasing of the information also makes the increasing in the computational burden which effect to the increasing in the complexity and also sensing time. On the contrary, blind detection technique does not require any prior knowledge about primary signal which make it is more flexible. The advantages of blind detection technique are less computational complexity, less time to perform sensing and can be applied to any pattern of primary signal. The disadvantage is the performance of detection, which degrade greatly at low Signal-to-Nosie Ratio (SNR).

Accuracy of detection can be evaluated through statistical models, including probability of detection (P_d), probability of false alarm (P_{fa}) and probability of misdetection (P_m). The probability of detection refers to correct declaration of a secondary user when a primary user actually presents or absents. The probability of false alarm refers to the declaration that a primary user presents when it actually absents. Conversely, the probability of misdetection refers to the declaration that a primary user absents when it actually presents. Target performance in perspective of an accuracy of detection is to maximize the probability of detection while the probability of false alarm and probability of misdetection should be minimized. The other performance metric is sensing time which is the duration that a secondary user performs spectrum sensing. IEEE 802.22 standard states that the duration to perform spectrum sensing is 2 seconds [43]. However, there is a tradeoff between duration to perform spectrum sensing and an accuracy of detection. In general, the secondary user should delicately perform spectrum sensing to achieve high accuracy of detection. This will make the system consumes more sensing time, more complexity and the system throughput also decreases.

To detect the existence of a PU, there are two hypothesis models of a received signal that are expressed as follows:

$$\mathbf{x} = \begin{cases} \boldsymbol{\eta} & \text{when a PU is absent } [H_0], \\ \mathbf{s} + \boldsymbol{\eta} & \text{when a PU is present } [H_1], \end{cases} \tag{2-3}$$

where $\mathbf{x}$ is the signal an SU receives, $\boldsymbol{\eta}$ is additive white Gaussian noise, and $\mathbf{s}$ is the signal transmitted by a PU.

In this section, we conclude the well-known spectrum sensing techniques including its own operational requirement and merits/demerits. Individual requirements and merits/demerits are briefly reviewed as follows:

A. Energy Detection

Energy detection (ED) is one of the most widely used techniques because it is easy to implement and does not require any prior knowledge about signal's pattern. However, the performance of detection degrade greatly at low SNRs. The average energy of received signal is define as a decision statistic which can be expressed as

$$\mathrm{Y_{ED}} = \frac{1}{N} \sum_{t=1}^{N} |\mathrm{x(t)}|^2 \tag{2-4}$$

where $\mathrm{Y_{ED}}$ and N denote test statistic and the sample interval, respectively. The threshold is determined by using probability of false alarm ($\mathrm{P_{fa}}$). In addition, probability of detection ($\mathrm{P_d}$) can also be used. Mathematical models of probability of false alarm and probability of detection are given by

$$\begin{aligned} \mathrm{P_{fa}} &= P[\mathrm{Y_{ED}} \geq \gamma_{\mathrm{ED}} | H_0] \\ &= \mathrm{Q}\left[\left(\frac{\gamma_{\mathrm{ED}}}{\sigma_{\mathrm{n}}{}^2} - 1\right)\sqrt{N}\right] \end{aligned} \tag{2-5}$$

$$\mathrm{P_d} = P[\mathrm{Y_{ED}} \geq \gamma_{\mathrm{ED}} | H_1]$$

$$= Q\left[\frac{\sqrt{N}}{\alpha+1}\left(\frac{\gamma_{\mathrm{ED}}}{\sigma_{\mathrm{n}}^{2}} - \alpha - 1\right)\right] \quad (2\text{-}6)$$

$$\alpha = \frac{\sigma_{\mathrm{s}}^{2}}{\sigma_{\mathrm{n}}^{2}}$$

where γ_{ED} denotes decision threshold, $\mathrm{Q}(.)$ is standard Gauss complementary cumulative distribution function, σ_{n}^{2} is the variance of noise, σ_{s}^{2} is the variance of desired signal. To determine the existence of primary user, the test statistic is compared to the threshold. The spectrum band is vacant if test statistic is less than the threshold

B. Matched Filter Detection

Matched filter detection (MFD) uses the correlation between the received and known signals. The output from MFD is compared to a threshold to determine the existence of a PU. The test statistic of MFD, Y_{MFD}, is given by

$$Y_{\mathrm{MFD}} = \sum_{n=0}^{N-1} x(n)\, s^{*}(n), \quad (2\text{-}7)$$

where $s^{*}(n)$ is the conjugate of the known signal. The decision threshold, γ_{MFD}, is determined from the probability of false alarm, $P_{\mathrm{fa(MFD)}}$. Alternatively, the probability of detection, $P_{\mathrm{d(MFD)}}$, can also be used as the decision threshold. Mathematical models for $P_{\mathrm{fa(MFD)}}$ and $P_{\mathrm{d(MFD)}}$ are given as

$$\begin{aligned} P_{\mathrm{fa(MFD)}} &= P[Y_{\mathrm{MFD}} \geq \gamma_{\mathrm{MFD}} | H_0] \\ &= Q\left[\left(\frac{\gamma_{\mathrm{MFD}}}{\sigma_{\eta}\sqrt{E}}\right)\right], \end{aligned} \quad (2\text{-}8)$$

$$\begin{aligned} P_{\mathrm{d(MFD)}} &= P[Y_{\mathrm{MFD}} \geq \gamma_{\mathrm{MFD}} | H_1] \\ &= Q\left[\left(\frac{\gamma_{\mathrm{MFD}} - E}{\sigma_{\eta}\sqrt{E}}\right)\right], \end{aligned} \quad (2\text{-}9)$$

where E is the energy of desired signal.

C. Maximum Eigenvalue Detection

Maximum eigenvalue detection (MED) is the sensing technique based on statistical covariance of the signal. Since the covariance matrix contains the correlation between signal samples, thus this detector calculate the maximum eigenvalue of covariance matrix and used as test statistic in order to determine the existence of primary user. A received signal comprising L consecutive samples is given by

$$\mathbf{x} = [x(n)\; x(n-1) \ldots x(n-L-1)]^{\mathrm{T}}, \quad (2\text{-}10)$$

$$\mathbf{s} = [s(n)\;\; s(n-1) \ldots s(n-L-1)]^{\mathrm{T}}, \quad (2\text{-}11)$$

$$\boldsymbol{\eta} = [\eta(n)\ \eta(n-1) \ldots \eta(n-L-1)]^{\mathrm{T}}, \tag{2-12}$$

where L is a smoothing factor. Since the statistical covariance matrix cannot be directly calculated, the sample covariance matrix of the received signal is computed by the following procedure:

1. The sample auto-correlations of the received signal are firstly expressed as

$$\varphi(l) = \frac{1}{N}\sum_{m=0}^{N-1} x(m)x(m-l)\,, \quad l = 0, 1, 2, \ldots, L-1. \tag{2-13}$$

2. Secondly, the sample covariance matrix of the received signal is calculated as

$$\mathbf{R}_{\mathbf{x}}(N) = \begin{bmatrix} \varphi(0) & \varphi(1) \cdots & \varphi(l-1) \\ \varphi(1) & \varphi(0) & \varphi(l-2) \\ \vdots & \ddots & \vdots \\ \varphi(l-1) & \cdots & \varphi(0)) \end{bmatrix}. \tag{2-14}$$

Note that the sample covariance matrix is a Toeplitz and symmetric matrix.

3. Thirdly, the eigenvalues of (2-14) are calculated using an eigen-decomposition algorithm. Note that only the maximum eigenvalue of the received signal, $\lambda_{\max}$, is used in step 4 to determine the existence of a PU.

4. Finally, the existence of a PU can now be determined from the value of $\lambda_{\max}$.

$$\lambda_{\max}(N) > \gamma_{\mathrm{MED}}{\sigma_{\boldsymbol{\eta}}}^2 \quad \text{when a PU is present,} \tag{2-15}$$
$$\lambda_{\max}(N) \le \gamma_{\mathrm{MED}}{\sigma_{\boldsymbol{\eta}}}^2 \quad \text{when a PU is absent,} \tag{2-16}$$

where γ_{MED} denotes a predetermined decision threshold.

Since the sample covariance matrix of the noise is nearly a Wishart random matrix, MED is analyzed using the probability distribution of the normalized largest eigenvalue — referred to as "Tracy–Widom distribution". Thereby, $P_{\mathrm{fa(MED)}}$ can be expressed as

$$\begin{aligned} P_{\mathrm{fa(MED)}} &= P\left[\lambda_{\max}(\mathbf{R}_{\boldsymbol{\eta}}(N)) > \gamma_{\mathrm{MED}}{\sigma_{\boldsymbol{\eta}}}^2\,\right] \\ &\approx\ 1 - F\left[\left(\frac{\gamma_{\mathrm{MED}}N-\rho}{v}\right)\right], \end{aligned} \tag{2-17}$$

$$\rho = \left(\sqrt{N-1} + \sqrt{L}\right)^2, \tag{2-18}$$

$$v = \left(\sqrt{N-1} + \sqrt{L}\right)\left(\frac{1}{\sqrt{N-1}} + \frac{1}{\sqrt{L}}\right)^{1/3}. \tag{2-19}$$

D. Covariance Absolute Value Detection

With covariance absolute value detection (CAV), an SU determines the existence of a PU from the received signal. This is done by comparing the auto-correlation of the received signal to the CAV threshold. However, CAV will perform poorly when the auto-correlation of the received signal is low. The test statistic of CAV, Y_{CAV}, is given by

$$Y_{\mathrm{CAV}} = \left(\varphi(0) + \frac{2}{L}\sum_{l=1}^{L-1}(L-l)|\varphi(l)|\right)\left(\varphi(0)\right)^{-1}. \tag{2-20}$$

The threshold for CAV detection, γ_{CAV}, can be expressed as

$$\gamma_{\mathrm{CAV}} = \left(1 + (L-1)\sqrt{\frac{2}{N\pi}}\right)\left(1 - Q^{-1}(P_{\mathrm{fa}})\sqrt{\frac{2}{N}}\right)^{-1}. \tag{2-21}$$

A PU is present if $Y_{\mathrm{CAV}} \geq \gamma_{\mathrm{CAV}}$. Mathematical models for $P_{\mathrm{fa(CAV)}}$ and $P_{\mathrm{d(CAV)}}$ are given as

$$P_{\mathrm{fa(CAV)}} = 1 - Q\left[\frac{\frac{1}{\gamma_{\mathrm{CAV}}}\left(1+(L-1)\sqrt{\frac{2}{N\pi}}\right)-1}{\sqrt{\frac{2}{N}}}\right], \tag{2-22}$$

$$P_{\mathrm{d(CAV)}} = 1 - Q\left[\frac{\frac{1}{\gamma_{\mathrm{CAV}}}+\left(\frac{\gamma_L\,\mathrm{SNR}}{\gamma_{\mathrm{CAV}}(\mathrm{SNR}+1)}\right)-1}{\sqrt{\frac{2}{N}}}\right], \tag{2-23}$$

where γ_L is given by

$$\gamma_L \triangleq \frac{2}{L}\sum_{l=1}^{L-1}(L-1)|\alpha_l| \tag{2-24}$$

and α_l is given by

$$\alpha_l = {E[\mathrm{s}(n)\mathrm{s}(n-l)]}\Big/{\sigma_{\mathrm{s}}}^2. \tag{2-25}$$

E. Maximum to Minimum Eigenvalue Detection

The procedure of maximum to minimum eigenvalue detection (MME) is similar to MED. However, the MME method determines the existence of a PU by comparing the ratio of the maximum and minimum eigenvalues with the threshold γ_{MME}. MME detection can be calculated using (2-14). The test statistic for the MME detection method is given by

$$Y_{\mathrm{MME}} = {}^{\lambda_{\max}}/_{\lambda_{\min}}. \tag{2-26}$$

The probability of false alarm for MME detection is given by

$$P_{\mathrm{fa(MME)}} \approx 1 - F\left[\frac{\gamma_{\mathrm{MME}}\left(\sqrt{N}+\sqrt{L}\right)^{2} - \rho}{v}\right]. \tag{2-27}$$

The threshold of the first stage can be expressed as

$$\gamma_{\mathrm{MME}} = \frac{F^{-1}(1-\mathrm{P_{fa}})v+\mu}{\left(\sqrt{\mathrm{N}}+\sqrt{L}\right)^{2}} \tag{2-28}$$

F. Leading Eigenvector Detection

Leading eigenvector detection (LED) calculates the correlation between the leading eigenvector of the received signal and the leading eigenvector of the known signal. Similar to MFD, the output is compared to a threshold to determine the existence of a PU. Since LED keeps only the most significant feature of the received signal, the technique requires less memory than MFD. However, since the LED technique needs to calculate the leading eigenvector of the received signal, the sensing time and complexity of computation is increased.

Let us define the following PU signals, $\mathbf{x}_i, i = 1, 2, \ldots, M$, each of which has d dimensions, as

$$\begin{aligned} \mathbf{x}_1 &= [x(n)\ x(n+1) \ldots\ x(n+d-1)]^{\mathrm{T}}, \\ \mathbf{x}_2 &= [x(n+1)\ x(n+2) \ldots\ x(n+d)]^{\mathrm{T}}, \\ &\vdots \\ \mathbf{x}_M &= [x(N+n-d)\ \ldots\ x(N+n-1)]^{\mathrm{T}}. \end{aligned} \tag{2-29}$$

The LED procedure can then be summarized as follows:

1. The sample covariance matrix of a received signal $\mathbf{x}_i$ is given by

$$\mathbf{R}_{\mathbf{x}} = \frac{1}{M}\sum_{i=1}^{M} \mathbf{x}_i \mathbf{x}_i^{\mathrm{T}}. \tag{2-30}$$

Note that we assume the sample mean to be zero.

2. The eigenvalues and eigenvectors of the received signal can be calculated using (2-30). Only an eigenvector corresponding to the largest eigenvalue, $\mathbf{v}_1$, is considered. The test statistic for LED is given by

$$Y_{\mathrm{LED}} = \max_{l=0,\,1,\,2,\,\dots\,,\,d} \left| \sum_{j=1}^{d} \mathbf{v}_1[j] \hat{\mathbf{v}}_1[j+l] \right|. \tag{2-31}$$

3. The existence of a PU can now be determined from the value of Y_{LED}.

$$Y_{\mathrm{LED}} > \gamma_{\mathrm{LED}} \text{ when a PU is present,} \tag{2-32}$$

$$Y_{\mathrm{LED}} \leq \gamma_{\mathrm{LED}} \text{ when a PU is absent,} \tag{2-33}$$

where $\hat{\mathbf{v}}_1$ is the leading eigenvector of the received signal, $\mathbf{v}_1$ is the leading eigenvector of the known signal, and γ_{LED} is a predetermined threshold.

2.3 Noise uncertainty

In practical communication system, noise may occurs from more than one sources. Then the variance of noise is difficult to be exactly estimated. Once noise occurs from various sources, the disturbance of noise is undesirable that is referred to an "uncertain behavior" or "noise uncertainty" [75]. The noise uncertainty may occur from the time-varying of thermal noise in a receiver and the non-linearity of the receiver. In addition, the transmission of other users also causes the noise uncertainty. When the uncertainty of noise occurs, the variance of noise distributes within range of $\left[\alpha {\sigma_{\boldsymbol{\eta}}}^2, \frac{1}{\alpha} {\sigma_{\boldsymbol{\eta}}}^2\right]$. Then, an estimated noise power can be expressed as

$$\hat{\sigma}_{\boldsymbol{\eta}}{}^2 = \alpha {\sigma_{\boldsymbol{\eta}}}^2 \tag{2-34}$$

where α is a noise uncertainty interval and ${\sigma_{\boldsymbol{\eta}}}^2$ is a noise variance. Then, noise uncertainty factor (in dB) distributes within range $[-B, B]$ when noise uncertainty factor (in dB) is given as

$$B = max\,\{10\log_{10}\alpha\}. \tag{2-35}$$

2.4 Path loss

In practical communication networks, the received signal power of the transmitted signal may be lower than its transmitted power due to an attenuation of signal strength (power) due to the propagation distance between PU and SU. This is referred to path loss [76-77]. The mathematical model of path loss is derived as

$$PL \equiv Cd^{-\aleph} \tag{2-36}$$

where PL is path loss, d is distance between PU and SU, C is loss constant and $\aleph$ is path loss exponent.

Then, the received SNR due to path loss effect can be expressed as

$$\tilde{\gamma}_{PL} = \frac{PL \cdot \sigma_{\mathbf{s}}^{2}}{\sigma_{\mathbf{\eta}}^{2}} \tag{2-37}$$

where $\sigma_{\mathbf{s}}^2$ is a signal variance.

2.5 Principal Component Analysis

Principal component analysis is a main trend in classical feature extraction and data compression method which data is represented in lower dimensionality (subspace) through linear transformation technique. PCA algorithm commonly used in the field of pattern recognition, such as face recognition and vehicle license plate recognition. The main objective of PCA algorithm is to reduce original data dimensionality by performing a covariance analysis between factors and eliminating the extrinsic features (or later principal components). In other words, PCA algorithm attempts to find significant features (or principal components) of the distribution of data. Through the computation of linear transformation, a new coordinate system is chosen for the data set comes to lie on the axis. Mathematical theory that used in PCA algorithm including standard deviation, covariance, eigenvectors, eigenvalues and also linear transformation.

PCA algorithm reduced the dimension of data while the variance in the original-dimensional space is preserved as much as possible. In addition, PCA algorithm perform this reduction with minimum mean square error compared to the desired data. In term of computation, the principal component can be found by performing computed the eigenvector and eigenvalue of covariance matrix of the data. Eigenvector corresponding to the largest eigenvalue represented the most significant feature of the data (principal component). In other words, the principal component is the direction (or axis on a new coordinate) of greatest variation which data can relied on. The second component is the orthogonal direction with the next highest variation (or eigenvalue) and so on.

Referring to face recognition, eigenface is a vital element that effectively represent face image using PCA algorithm. The main concept of eigenface is to reconstruct any collected face images using the weight combination of significant features of images which obtained from the collection. Thus, eigenfaces can be defined as the principal directions of all possible face images in a new coordinate systems. Referring to face recognition, eigenface is a vital element that effectively represent face image using PCA algorithm. The main concept of eigenface is to reconstruct any collected face images using the weight combination of significant features of images which obtained from the collection. Thus, eigenfaces can be defined as the principal directions of all possible face images in a new coordinate systems. Training operations of face recognition can be summarized as the following:

The PCA algorithm can be summarized as follow.

1. Obtain images $U_1, U_2, \ldots, U_N$

2. Represent every image U_i as vector I_i
3. Compute the average of image vector (μ):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_i \tag{2-38}$$

4. Subtract the mean image (γ_i):

$$\gamma_i = I_i - \mu \tag{2-39}$$

5. Compute the covariance matrix (C) :

$$C = \frac{1}{N}\sum_{i=1}^{N} \gamma_i {\gamma_i}^T \tag{2-40}$$

6. Compute the eigenvectors ($V = [v_1, v_2, \dots, v_K]$) and eigenvalues ($u$) of C. Where eigenvectors (V) known as eigenfaces or eigenspace.
7. Keep only K best eigenvectors corresponding to the K largest eigenvalues.
8. Each image (subtract the mean image: γ_i) in the training set can be represented as a linear combination of the K best eigenvectors:

$$\gamma_i - \mu = \sum_{j=1}^{K} \tilde{x}_j \, v_i \tag{2-41}$$

or

$$\tilde{x}_j = {v_i}^T \gamma_i \tag{2-42}$$

9. Represent γ_i as $\tilde{x} = \begin{bmatrix} {\tilde{x}_1}^i \\ {\tilde{x}_2}^i \\ \vdots \\ {\tilde{x}_K}^i \end{bmatrix}$ (2-43)

It is clear that 95% of the total number of features present in the images is a sufficient amount to be representative of all the existing features. Hence, having decided to only select the k best eigenvectors, the dimension of the images is reduced. Reducing the dimension of the WM signals avoids a huge amount of computational burden. Moreover, the effect of noise from the original signal is avoided due to the reduction in dimension of the images.

For given an unknown image (I_{test}) follows these procedure.

1. Normalize I: $\gamma_{test} = I_{test} - \mu$ (2-44)

2. Project on the eigenspace: $\gamma_{test} - \mu = \sum_{j=1}^{K} \tilde{x}_j \, v_i$ (2-45)

3. Represent γ_{test} as $\tilde{x}_{test} = \begin{bmatrix} \tilde{x}_{1,test} \\ \tilde{x}_{2,test} \\ \vdots \\ \tilde{x}_{K,tset} \end{bmatrix}$.

Chapter 3

Proposed Techniques

In this chapter, we descript four spectrum sensing techniques that we are proposed. Two methods are double-constrain adaptive energy detection (DCAED) and fast spectrum sensing with coordinate system (FSC) for additive white Gaussian noise (AWGN) channel. Two techniques are two-stage spectrum sensing and modified FSC for noise uncertainty and path loss environment.

3.1 Double constraints adaptive energy detection

From chapter 2, we known that ED [60-63] is the most widely utilized because it consumes the shortest sensing time with the least complexity. However, the accuracy of detection of ED is unreliable under bad condition of communication channel or at low signal to noise ratio (SNR) condition. In [64, 65], the performance of ED is improved by using an adaptive threshold. In general, the threshold of ED is set by fixing target performance metrics. There are 2 ways to set a threshold for ED. The first way is done by fixing target probability of false alarm which is called “constant false alarm rate (CFAR)”. The other way is done by fixing target probability of detection which is called “constant detection rate (CDR)”. An adaptive threshold energy detection (ATED) changes its decision threshold depending on the condition of communication channel. The system threshold switches between the threshold of CFAR and CDR. Although the detection performance of ED is improved, the false alarm detection rate does not achieve the target performance stated by IEEE 802.22 standard which the spectrum sensing technique has to perform spectrum sensing with probability of false detection less than 0.1.

3.1.1 Conventional energy detection technique

As shown in Figure3-1, the PU signal is received by SU. The output from bandpass filter is digitized by analog to digital converter (ADC). The existence of PU is determined by measuring the energy of the received signal and compares to predetermined threshold.

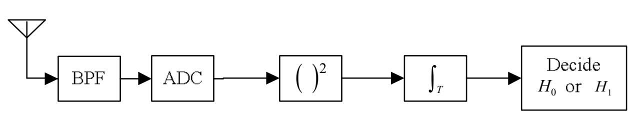


Figure 3-1 Model of conventional energy detection technique [64].

The decision statistic of ED is given as

$$Y_{\mathrm{ED}} = \frac{1}{N} \sum_{n=1}^{N} |\mathbf{x}(n)|^2. \tag{3-1}$$

When the PU absents, the decision statistic can be represented as

$$Y_{\mathrm{ED}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} |\boldsymbol{\eta}\ (\mathrm{n})|^2. \tag{3-2}$$

If both of primary signal and noise is an independent and identically distributed (i.i.d.) random process. The mean (μ_0) and variance ${\sigma_0}^2$ under hypothesis H_0 can be derived as

$$\mu_0 = E|Y_{\mathrm{ED}}| = \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} |\boldsymbol{\eta}\ (\mathrm{n})|^2$$

$$= \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} {\sigma_{\boldsymbol{\eta}}}^2 = {\sigma_{\boldsymbol{\eta}}}^2 \tag{3-3}$$

$${\sigma_0}^2 = E|Y_{\mathrm{ED}} - \mu_0|^2 = \frac{1}{\mathrm{N}} \left|E|\boldsymbol{\eta}\ (\mathrm{n})|^4 - {\sigma_{\boldsymbol{\eta}}}^4\right|. \tag{3-4}$$

If Gaussian noise is real-valued, $E|\boldsymbol{\eta}\ (\mathrm{n})|^4 = 3{\sigma_{\boldsymbol{\eta}}}^2$. The variance ${\sigma_0}^2$ can be expressed as

$${\sigma_0}^2 = \sqrt{\frac{2}{N}}{\sigma_{\boldsymbol{\eta}}}^2. \tag{3-5}$$

Thus, the probability of false alarm ($\mathrm{P_{fa}}$) can be expressed as

$$\mathrm{P_{fa}} = Q\left(\left(\frac{\lambda}{{\sigma_{\boldsymbol{\eta}}}^2} - 1\right)\sqrt{\frac{N}{2}}\right) \tag{3-6}$$

where λ is decision threshold, ${\sigma_{\boldsymbol{\eta}}}^2$ is the variance of noise and ${\sigma_{\mathbf{s}}}^2$ is the variance of primary user signal and $Q(\cdot)$ is standard Gauss complementary cumulative distribution function.

When the PU presents (H_1), the decision statistic is given as

$$Y_{\mathrm{ED}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} |\mathbf{s}(\mathrm{n}) + \boldsymbol{\eta}\ (\mathrm{n})|^2 \tag{3-7}$$

Under hypothesis H_1, the mean (μ_1) can be derived as

$$\mu_1 = E|Y_{\mathrm{ED}}| = \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} |\mathbf{s}(\mathrm{n}) + \boldsymbol{\eta}\ (\mathrm{n})|^2$$

$$= {\sigma_{\mathbf{s}}}^2 + {\sigma_{\boldsymbol{\eta}}}^2 = (\gamma + 1){\sigma_{\boldsymbol{\eta}}}^2 \tag{3-8}$$

$$\gamma = \frac{{\sigma_{\mathbf{s}}}^2}{{\sigma_{\boldsymbol{\eta}}}^2} \tag{3-9}$$

where γ represents signal-to-noise ratio (SNR). The variance ${\sigma_1}^2$ is given as

$${\sigma_1}^2 = E|Y_{\mathrm{ED}} - \mu_1|^2 \tag{3-10}$$

$$= \frac{1}{\mathrm{N}} \left|E|\mathbf{s}\ (\mathrm{n})|^4 + E|\boldsymbol{\eta}\ (\mathrm{n})|^4 - \left({\sigma_{\mathbf{s}}}^2 - {\sigma_{\boldsymbol{\eta}}}^2\right) + 2{\sigma_{\mathbf{s}}}^2{\sigma_{\boldsymbol{\eta}}}^2\right|$$

If Gaussian noise is real-valued, $E|\mathbf{s}(\mathrm{n})|^4 = 3\sigma_{\mathbf{s}}{}^2$ and $E|\boldsymbol{\eta}\,(\mathrm{n})|^4 = 3\sigma_{\boldsymbol{\eta}}{}^2$. The variance $\sigma_1{}^2$ can be expressed as

$$\sigma_1{}^2 = \sqrt{\frac{2}{N}}(\gamma + 1)\sigma_{\boldsymbol{\eta}}{}^2. \tag{3-11}$$

Thus, the probability of detection $(\mathrm{P_d})$ can be represented as

$$\mathrm{P_d} = Q\left[\frac{\sqrt{\mathrm{N}/2}}{\gamma+1}\left(\frac{\lambda}{\sigma_{\boldsymbol{\eta}}{}^2} - \gamma - 1\right)\right]. \tag{3-12}$$

There are 2 ways to set the threshold for ED technique. The first technique is called CFAR which the threshold is set by fixing $\mathrm{P_{fa}}$. Thus, the threshold for CFAR can be computed by

$$\lambda_{CFAR} = \left(Q^{-1}(\mathrm{P_{fa}})\sqrt{\frac{2}{N}} + 1\right)\sigma_{\boldsymbol{\eta}}{}^2. \tag{3-13}$$

To set the threshold by fixing $\mathrm{P_d}$, which is called CDR, can be done by

$$\lambda_{CDR} = \left(\sqrt{\frac{2}{N}}(\gamma + 1)Q^{-1}(\mathrm{P_d}) + \gamma + 1\right)\sigma_{\boldsymbol{\eta}}{}^2. \tag{3-14}$$

However, it should be realized that the predetermined thresholds (λ_{CDR} and λ_{CFAR}) are set by fixing only a single target performance metric. Thus, there is always be a tradeoff in the performance of ED technique by fixing only a single target performance metric. ED with threshold based on CDR gives poor detection performance in perspective of $\mathrm{P_{fa}}$. Conversely, ED with threshold based on CFAR gives poor detection performance in perspective of $\mathrm{P_d}$.

3.1.2 Adaptive threshold energy detection

From [63, 64], the adaptive threshold energy detection (ATED) technique was proposed. The adaptive parameter (α) was introduced to vary the threshold depending on the condition of communication channel. As shown is Figure 3-2, the SNR estimator plays as an important part of the system. The SNR estimator estimates the variance noise from the received signal and sends it to the threshold setter device. The threshold setter device generates a new threshold which is appropriate to the communication channel at the period of time

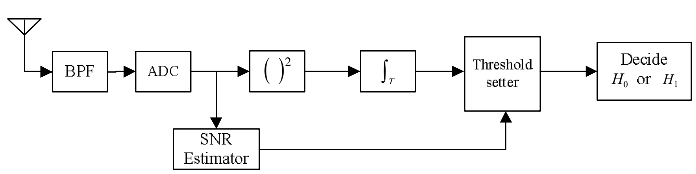


Figure 3-2 Model of adaptive threshold energy detection technique [64]

The new threshold is given by

$$\lambda = \lambda_{CFAR} + \alpha * (\lambda_{CDR} - \lambda_{CFAR}), 0 \leq \alpha \leq 1. \quad (3\text{-}15)$$

The adaptive parameter (α) is set depending on the condition of communication channel. Since the SNR of communication channel is estimated, the system calculates the critical sample which is appropriate to the communication channel at the period of time. If the number of sample of the system is lower than the number of critical sample, the adaptive parameter (α) is set to be 1. On the other hand, if the number of sample of the system is greater than the number of critical sample, the adaptive parameter (α) is set to be 0. In addition, the value of adaptive parameter (α) can be change between 0 to 1.

3.1.3 Double constraints adaptive energy detection

In this section, double constraint adaptive energy detection (DCAED) is explained. DCAED exploits an interdependent between $\mathrm{P_{fa}}$ and $\mathrm{P_d}$ to generate a new adaptive factor (β). However, there is no directly way to set the threshold by fixing $\mathrm{P_{fa}}$ and $\mathrm{P_d}$ as the target performance metrics. DCAED sets the adaptive factor (β) by using the critical sample (N_c), since N_c retains the independent between $\mathrm{P_{fa}}$ and $\mathrm{P_d}$. Then adaptive factor is used to set the threshold in order to achieve target performance metrics.

The system model is shown in Figure 3-3. The information from SNR estimator is gathered by adaptive threshold device. The estimated SNR value is compared to critical SNR (γ_c). If the estimated value is greater than critical value (γ_c) means that the commination channel is in a good condition which conventional ED offers a reliable detection performance. Thus, the adaptive factor (β) is set to make the system remains the new threshold as predetermined threshold. On the other hand, if the estimated value is lower than critical value, the new threshold is generated by setting the adaptive factor (β) depending on the condition of communication channel.

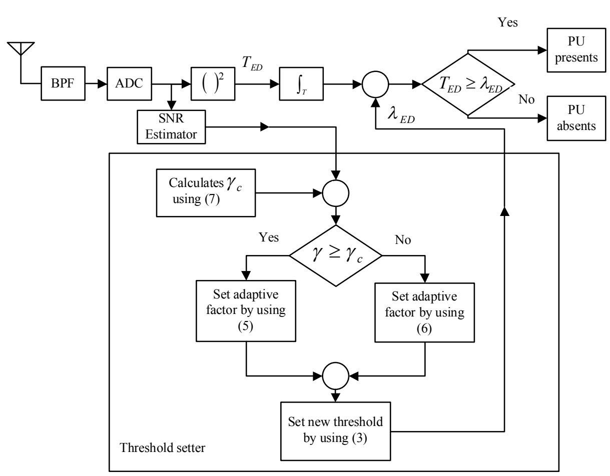


Figure 3-3 Model of DCAED.

The threshold is given as

$$\lambda_{New} = \beta \sigma_{\mathbf{est}}{}^{2}\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_{\mathbf{\eta}}{}^{2}} - 1\right) + \sigma_{\mathbf{est}}{}^{2} \tag{3-16}$$

where $\sigma_{\mathbf{est}}{}^{2}$ is an estimated noise variance .

N_c refers to a minimum number of sample that is required by conventional energy detection technique to meet the target performance metrics ($\mathrm{P_{fa}}$ and $\mathrm{P_d}$). By using (3-6) and (3-12), the interdependent between these parameters can be shown as

$$\mathrm{P_{fa}} = Q\left(Q^{-1}(\mathrm{P_d})(\gamma+1) + \gamma\sqrt{\frac{N}{2}}\right) \tag{3-17}$$

$$\mathrm{P_d} = Q\left(\frac{1}{(\gamma+1)}\left(Q^{-1}(\mathrm{P_{fa}}) - \gamma\sqrt{\frac{N}{2}}\right)\right). \tag{3-18}$$

By solving (3-6) and (3-12), the critical sample (N_c) can be expressed as

$$N_c = \frac{2}{\gamma^2}\left[Q^{-1}(\mathrm{P_{fa}}) - Q^{-1}(\mathrm{P_d})(\gamma+1)\right]^2. \tag{3-19}$$

From the definition of critical sample, we can conclude that if we set the new threshold by changing the sample (N) to critical sample (N_c) in (3-13) or (3-14). The performance of ED will meet the target performance metrics. However, it is not feasible to change the sample to the desired number in practical. Thus, DCAED meets the target accuracy of detection performance metrics as changing critical sample by using the adaptive factor to change the system threshold.

By solving (3-6), (3-17) and (3-19) under condition of the proposed scheme. The adaptive factor (β) of the system can be expressed as

$$\beta = \begin{cases} \dfrac{\lambda_{\mathrm{CFAR}} - \sigma_{\mathbf{est}}{}^{2}}{\left(\frac{\lambda_{\mathrm{CFAR}}}{\sigma_{\mathbf{\eta}}{}^{2}} - 1\right)\sigma_{\mathbf{est}}{}^{2}} & , \gamma \geq \gamma_c \quad [C_0] \quad (3-20) \\ \dfrac{\gamma\sqrt{N/2}}{(Q^{-1}(\mathrm{P_{fa}}) - Q^{-1}(\mathrm{P_d})(\gamma+1))} & , \gamma < \gamma_c \quad [C_1] \quad (3-21) \end{cases}$$

where C_0 is the condition that estimated SNR is greater than critical SNR and C_1 is the condition that estimated SNR is lower than critical SNR.

In addition, the critical SNR (γ_c) for the system is given by

$$\gamma_c = \frac{Q^{-1}(\mathrm{P_{fa}}) - Q^{-1}(\mathrm{P_d})}{Q^{-1}(P_{\mathrm{d}}) - \sqrt{\frac{N}{2}}}. \tag{3-22}$$

3.2 Fast Spectrum Sensing with Coordinate System

In this section, we describe in detail with mathematical models of the fast spectrum sensing with coordinate system (FSC) algorithm. The FSC algorithm is a spectrum sensing technique that requires prior knowledge of a PU's signals. The framework for the FSC algorithm can be categorized into two phases — coordinate system construction and sensing. The coordinate system must be predetermined from the two most significant features of WM signals and kept in the knowledge base. The sensing phase determines the existence of a PU by comparing the FSC decision statistic (Y_{FSC}) to the FSC threshold (γ_{FSC}). The decision statistic is calculated by projecting the PU's signal onto the predetermined coordinate system.

Following the PCA algorithm, the WM signals are first decomposed into a small set of features. The significance of each feature can then be explained by an eigenvector and eigenvalue, where the eigenvector represents the direction of the feature and the eigenvalue explains the variance of the WM signals in that direction. Therefore, the eigenvector corresponding to the highest eigenvalue represents the direction in which most of the data within the WM signals are varying. This eigenvector refers to the most significant feature of WM signals.

3.2.1 Coordinate System Construction

In this section, our coordinate system is introduced. The new coordinate system is of a lower dimension than the original data space. The main objectives of this phase are to select the two most significant features of WM signals and to construct a coordinate system. Our coordinate system construction process (as shown in Figure 3-4) exploits the feature extraction and selection process of a PCA algorithm [66-67] to filter out the two most significant features of WM signals and then uses them as the axes for a new coordinate system. Due to the smaller size of the new coordinate system, the FSC algorithm consumes less memory, has less computational burden, and has a short sensing time.

We assume that the WM signals of a PU are known to an SU. These WM signals are used as the *training* signals. Let the vectors $\mathbf{s}_1$, $\mathbf{s}_2$,..., $\mathbf{s}_M$ represent WM signals. These vectors are referred to as *training* vectors. The training vectors are given by

$$\begin{aligned} \mathbf{s}_1 &= [s_1(1)\ s_1(2) \dots s_1(N)]^{\mathrm{T}}, \\ \mathbf{s}_2 &= [s_2(1)\ s_2(2) \dots s_2(N)]^{\mathrm{T}}, \\ &\vdots \\ \mathbf{s}_M &= [s_M(1)\ s_M(2) \dots s_M(N)]^{\mathrm{T}}. \end{aligned} \tag{3-23}$$

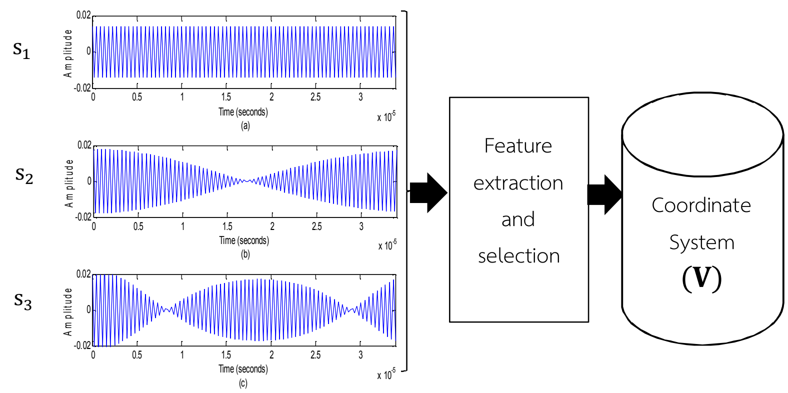


Figure 3-4 Coordinate system construction phase of FSC algorithm.

The procedure for the coordinate system construction phase is described as follows.

A. Feature Extraction

Firstly, we eliminate the common features of the WM signals by subtracting the average WM signals vector ($\boldsymbol{\varepsilon}$) from each training vector ($\mathbf{s}_i$).

$$\boldsymbol{\beta}_{\mathrm{i}} = \mathbf{s}_i - \boldsymbol{\varepsilon}, \tag{3-24}$$

where $\boldsymbol{\beta}_i$ is a vector that contains the significant features of the WM signals. The average WM signals vector ($\boldsymbol{\varepsilon}$) can be expressed as

$$\boldsymbol{\varepsilon} = \frac{1}{M}\sum_{i=1}^{M} \mathbf{s}_i. \tag{3-25}$$

Next, we compute the covariance matrix ($\mathbf{C}$) of $\boldsymbol{\beta}_i$, which is given by

$$\mathbf{C} = \frac{1}{M}\sum_{i=1}^{M} \boldsymbol{\beta}_i \boldsymbol{\beta}_i^{\mathrm{T}}. \tag{3-26}$$

From the covariance matrix, a matrix of eigenvectors ($\mathbf{V} = [\mathbf{v}_1\ \mathbf{v}_2 \ldots \mathbf{v}_d]$) and a vector of corresponding eigenvalues ($\boldsymbol{\lambda} = [\lambda_1\ \lambda_2 \ldots \lambda_d]^{\mathrm{T}}$) can be obtained by using the aforementioned eigen-decomposition algorithm.

B. Feature Selection

From the matrix of eigenvectors ($\mathbf{V}$), we keep only the k *best* eigenvectors (that is, those that correspond to the k largest eigenvalues), and the resulting set is then used to form the new coordinate system. The k best eigenvectors are determined by

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{d} \lambda_i} \geq 95\%, \tag{3-27}$$

where d is the number of eigenvalues in set λ.

From our investigation, we found that eigenvectors that had a correspondingly high eigenvalue more effectively represented the features of the WM signals than those eigenvectors that had correspondingly small eigenvalues. It is clear that 95% of the total number of features present in the WM signals is a sufficient amount to be representative of all the existing features. Hence, having decided to only select the k best eigenvectors, the dimension of the WM signals is reduced. Reducing the dimension of the WM signals avoids a huge amount of computational burden. Moreover, the effect of noise from the original signal is avoided due to the reduction in dimension of the WM signals Furthermore, the FSC algorithm is tolerant to noise.

3.2.2 Sensing Phase

In the sensing phase (see Figure 3-5), the weight of correspondence between the received WM signal and the new coordinate system is calculated by projecting the received signal onto the coordinate system. This weight describes the distribution of the received signal in the new coordinate system. The weight, given as a vector ($\hat{\mathbf{x}}$), can be expressed as

$$\hat{\mathbf{x}} = \mathbf{V}^{\mathrm{T}}(\mathbf{x} - \boldsymbol{\varepsilon}). \tag{3-28}$$

The magnitude of the weight vector is defined as the FSC decision statistic (Y_{FSC}). The magnitude of the weight vector will rise when a PU is present. Otherwise, the magnitude of the weight vector will fall when a PU is not present. The FSC decision statistic (Y_{FSC}) can be expressed as

$$Y_{\mathrm{FSC}} = \|\hat{\mathbf{x}}\|^2 = \left(\sqrt{\textstyle\sum_{i=1}^{k}(\hat{\mathbf{x}})^2}\right)^2 = \textstyle\sum_{i=1}^{k}(\hat{\mathbf{x}})^2. \tag{3-29}$$

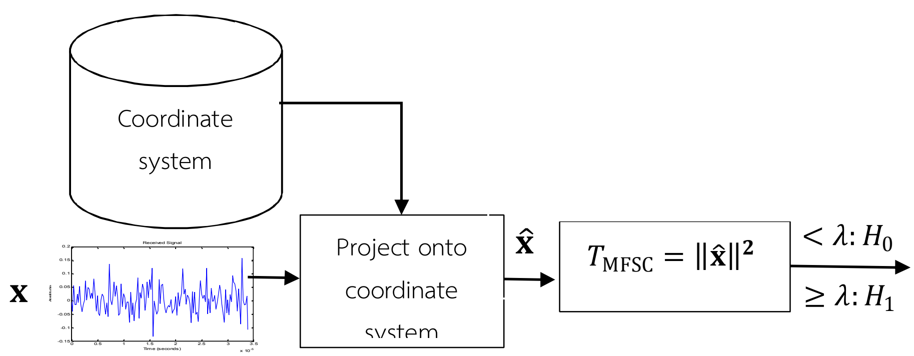


Figure 3-5 Sensing phase of FSC algorithm.

A mathematical model for the probability of false alarm of the FSC algorithm is given by

$$P_{\mathrm{fa(FSC)}} = P[Y_{\mathrm{FSC}} \geq \gamma_{\mathrm{FSC}} | H_0]. \tag{3-30}$$

Under condition H_0,

$$\hat{\mathbf{x}}_{\boldsymbol{\eta}} = \mathbf{V}^T(\mathbf{x}_{\boldsymbol{\eta}} - \boldsymbol{\varepsilon}). \tag{3-31}$$

$$Y_{\mathrm{FSC}} = \|\hat{\mathbf{x}}_{\boldsymbol{\eta}}\|^2 = \left(\sqrt{\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\boldsymbol{\eta}}\right)^2}\right)^2 = \textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\boldsymbol{\eta}}\right)^2, \tag{3-32}$$

$$\mu_{H_0} = \mathrm{E}[Y_{\mathrm{FSC}}] = \mathrm{E}\left[\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\boldsymbol{\eta}}\right)^2\right] = k\mathfrak{m}'_{2,H_0}, \tag{3-33}$$

$$\sigma_{H_0}^2 = \mathrm{Var}\left[\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\boldsymbol{\eta}}\right)^2\right] = k\left(\mathfrak{m}'_{4,H_0} - \left(\mathfrak{m}'_{2,H_0}\right)^2\right), \tag{3-34}$$

$$P_{\mathrm{fa(FSC)}} = Q\left[\left(\frac{\gamma_{\mathrm{FSC}} - k\mathfrak{m}'_{2,H_0}}{\sqrt{k\left(\mathfrak{m}'_{4,H_0} - \left(\mathfrak{m}'_{2,H_0}\right)^2\right)}}\right)\right]. \tag{3-35}$$

Note that μ_{H_i} is the mean value of H_i and that $\mathfrak{m}'_n$ is the n^{th} order moment of the FSC decision statistic (Y_{FSC}).

Similar to the probability of false alarm, the probability of detection for the FSC algorithm can be expressed as

$$P_{\mathrm{d(FSC)}} = P[Y_{\mathrm{FSC}} \geq \gamma_{\mathrm{FSC}} | H_1]. \tag{3-36}$$

Under condition H_1,

$$\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}} = \mathbf{V}^{\mathrm{T}}(\mathbf{x}_{\mathbf{s}+\boldsymbol{\eta}} - \boldsymbol{\varepsilon}), \tag{3-37}$$

$$Y_{\mathrm{FSC}} = \|\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}\|^2 = \left(\sqrt{\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}\right)^2}\right)^2 = \textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}\right)^2, \tag{3-38}$$

$$\mu_{H_1} = \mathrm{E}[Y_{\mathrm{FSC}}] = \mathrm{E}\left[\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}\right)^2\right] = k\mathfrak{m}'_{2,H_1}, \tag{3-39}$$

$$\sigma_{H_1}^2 = \mathrm{Var}\left[\textstyle\sum_{i=1}^{k}\left(\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}\right)^2\right] = k\left(\mathfrak{m}'_{4,H_1} - \left(\mathfrak{m}'_{2,H_1}\right)^2\right), \tag{3-40}$$

$$P_{\mathrm{d(FSC)}} = Q\left[\left(\frac{\gamma_{\mathrm{FSC}} - k\mathfrak{m}'_{2,H_1}}{\sqrt{k\left(\mathfrak{m}'_{4,H_1} - \left(\mathfrak{m}'_{2,H_1}\right)^2\right)}}\right)\right]. \tag{3-41}$$

In addition, the probability of misdetection of the FSC algorithm is given by

$$P_{\mathrm{m(FSC)}} = 1 - P_{\mathrm{d(FSC)}}. \tag{3-42}$$

3.3 Two-stage spectrum sensing

In this section, the proposed two-stage spectrum sensing algorithms are explained. Our proposed two-stage spectrum sensing algorithms (as depicted in Figure 3-6) exploit the merits of ED CAV and MME technique.

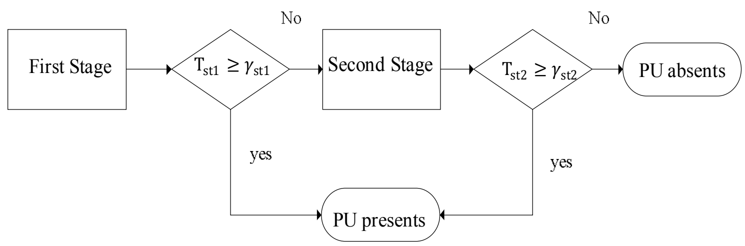


Figure 3-6 Two-stage spectrum sensing scheme [53].

The scheme of the proposed two-stage spectrum sensing techniques can be separated into 2 stages including coarse sensing stage and fine sensing stage. Mathematical models of overall probability of false alarm and overall probability of detection for two-stage spectrum sensing are given by

$$P_{fa} = P_{fa,1^{st}} + (1 - P_{fa,1^{st}})\, P_{fa,2^{nd}} \tag{3-43}$$

$$P_{d} = P_{d,1^{st}} + (1 - P_{d,1^{st}})\, P_{d,2^{nd}} \tag{3-44}$$

where P_{fa} is P_{fa} of the system, P_d is P_d of the system, $P_{fa,1^{st}}$ is P_{fa} of the first stage, $P_{fa,2^{nd}}$ is P_{fa} of the second stage, $P_{d,1^{st}}$ is P_d of the first stage and $P_{d,2^{nd}}$ is P_d of the second stage.

For a given channel, the existence of primary user is firstly determined by the first stage. Similar to other two-stage spectrum sensing techniques [52, 73], ED is utilized as the first stage. Although ED offers inaccurate detection at low SNR and when uncertainty noise power occurs, it performs spectrum sensing within short time. In addition, at high SNR environment, ED offers an accurate detection. If an average energy of received signal is greater than the threshold (γ_{ED}) then the spectrum band is declared to be presented. If the average energy of received signal is lower than γ_{ED}, the second stage is activated. The threshold of the first stage can be expressed as

$$\gamma_{ED} = \left(Q^{-1}\left(\frac{P_{fa,ED}}{\sqrt{N}}\right) + 1\right) \sigma_{\eta}{}^{2} \tag{3-45}$$

In our proposed algorithm, MME and CAV are utilized as a second stage. For ED to CAV two-stage spectrum sensing technique, after the second stage is activated, the statistical covariance of the signal sample is computed by (2-20). If the statistical covariance of the signal sample is lower than the threshold (2-21), the two-stage spectrum sensing technique determines that primary user absents. If the statistical covariance of the signal sample is greater than the threshold, the two-stage spectrum sensing technique determines that primary user presents.

For ED to MME two-stage spectrum sensing technique, after the second stage is activated, the maximum and minimum eigenvalue of covariance matrix of signal sample is computed by (2-14). If the ratio of maximum to minimum eigenvalue is lower than the threshold (2-28), the two-stage spectrum sensing technique determines that primary user absents. Otherwise, the two-stage spectrum sensing technique determines that primary user presents.

3.4 Modified- fast spectrum sensing with coordinate system (MFSC)

In this section, we both derive the mathematical model and describe the framework of modified- fast spectrum sensing with coordinate system (MFSC), which is modified from FSC (section 3.2), under path loss effect and noise uncertainty. The framework of MFSC algorithm is separated into two phases including coordinate system construction and sensing like FSC. Firstly, the coordinate system must be predetermined by keeping the two most significant features of WM signals. The sensing phase determines the existence of a PU by comparing the MFSC decision statistic (T_{MFSC}), where T_{MFSC} is calculated by projecting the received signal onto the coordinate system, to the MFSC threshold (λ_{MFSC}).

3.4.1 Coordinate System Construction

To construct a coordinate system, the known WM signals are decomposed into a set of features. Only the two most significant features are obtained and used as the axes of the coordinate system. The significance of each feature is explained by the eigenvector which is corresponding to the maximum eigenvalue.

Lets $\mathbf{s}_{\mathrm{i}}$ is a vector that represents WM signal. This vector is known as *training* vector. The training vectors are given by

$$\begin{aligned} \mathbf{s}_1 &= [s_1(1)\ s_1(2) \dots s_1(N)]^{\mathrm{T}}, \\ \mathbf{s}_2 &= [s_2(1)\ s_2(2) \dots s_2(N)]^{\mathrm{T}}, \\ &\vdots \\ \mathbf{s}_M &= [s_M(1)\ s_M(2) \dots s_M(N)]^{\mathrm{T}}. \end{aligned} \tag{3-46}$$

The procedure of the coordinate system construction can be summarized as the following

Firstly, the common features of the WM signals is eliminated by subtracting the average WM signals vector ($\boldsymbol{\varepsilon}$) from each training vector ($\mathbf{s}_i$).

$$\boldsymbol{\beta}_{\mathrm{i}} = \mathbf{s}_i - \boldsymbol{\varepsilon}, \tag{3-47}$$

where $\boldsymbol{\beta}_i$ is a vector that contains the significant features of the WM signals. The average WM signals vector ($\boldsymbol{\varepsilon}$) can be expressed as

$$\boldsymbol{\varepsilon} = \frac{1}{M}\sum_{i=1}^{M} \mathbf{s}_i. \tag{3-48}$$

Next, the covariance matrix ($\mathbf{C}$) of $\boldsymbol{\beta}_i$ is computed. Therefore, the covariance matrix ($\mathbf{C}$) is given by

$$\mathbf{C} = \frac{1}{M}\sum_{i=1}^{M} \boldsymbol{\beta}_i \boldsymbol{\beta}_i^{\mathrm{T}}. \tag{3-49}$$

Using the eigen-decomposition algorithm, a matrix of eigenvectors ($\mathbf{V} = [\mathbf{v}_1\ \mathbf{v}_2\ \ldots\ \mathbf{v}_d]$) and a vector of corresponding eigenvalues ($\boldsymbol{e} = [e_1\ \ e_2\ \ldots\ e_d]^{\mathrm{T}}$) are obtained. Finally, only the k *best* eigenvectors corresponding to the k largest eigenvalues are used to form the coordinate system. The number of k can be determined by

$$\frac{\sum_{i=1}^{k} e_i}{\sum_{i=1}^{d} e_i} \geq 95\%, \tag{3-50}$$

where d is the number of eigenvalues in set $\boldsymbol{e}$.

3.4.2 Sensing Phase

The weight vector ($\hat{\mathbf{x}}$) is given as

$$\hat{\mathbf{x}} = \mathbf{V}^{\mathrm{T}}(\mathbf{x} - \boldsymbol{\varepsilon}). \tag{3-51}$$

and $\mathbf{x}$ is SU received signal under noise uncertainty.

Finally, the magnitude of the weight vector is calculated and used as the MFSC decision statistic (T_{MFSC}). Therefore, the MFSC decision statistic (T_{MFSC}) can be expressed as

$$T_{\mathrm{MFSC}} = \|\hat{\mathbf{x}}\|^2 = \left(\sqrt{\sum_{i=1}^{k}(\hat{\mathbf{x}})^2}\right)^2 = \sum_{i=1}^{k}(\hat{\mathbf{x}})^2. \tag{3-52}$$

To determine the existence of PU, the MFSC decision statistic is compared to the MFSC threshold (λ_{MFSC}).

As mention earlier, the threshold is needed to be vary on the strength of path loss effect. From our investigation, we found that the changing in the signal's amplitude does not affect changing in the signal's feature (eigenvector) but affects changing in the average vector ($\boldsymbol{\varepsilon}$). Thus, the weight vector under path loss effect when the PU does not exist can be expressed as

$$\hat{\mathbf{x}}_{\boldsymbol{\eta}} = \mathbf{V}^{T}(\mathbf{x}_{\boldsymbol{\eta}} - \hat{\boldsymbol{\varepsilon}}), \tag{3-53}$$

where the average vector ($\boldsymbol{\varepsilon}$) under path loss effect is given by

$$\hat{\boldsymbol{\varepsilon}} = \sqrt{PL}\boldsymbol{\varepsilon}. \tag{3-54}$$

The probability of false alarm (P_{fa}) of the MFSC algorithm is given by

$$P_{\mathrm{fa}} = Q\left[\left(\frac{\lambda_{\mathrm{MFSC}} - k\mathfrak{m}'_{2,\hat{\mathbf{x}}_{\boldsymbol{\eta}}}}{\sqrt{k\left(\mathfrak{m}'_{4,\hat{\mathbf{x}}_{\boldsymbol{\eta}}} - \left(\mathfrak{m}'_{2,\hat{\mathbf{x}}_{\boldsymbol{\eta}}}\right)^2\right)}}\right)\right]. \tag{3-55}$$

where $\mu_{\hat{\mathbf{x}}_{\boldsymbol{\eta}}}$ is the mean value of $\hat{\mathbf{x}}_{\boldsymbol{\eta}}$ and that $\mathfrak{m}'_n$ is the n^{th} order moment of $\hat{\mathbf{x}}_{\boldsymbol{\eta}}$.

In general, the system threshold is set by fixing the target P_{fa} , then the MFSC threshold (λ_{MFSC}) is given by

$$\lambda_{\mathrm{MFSC}} = Q^{-1}(P_{\mathrm{fa}})\sqrt{k\left(\mathfrak{m}'_4 - \left(\mathfrak{m}'_{2,H_0}\right)^2\right)} + k\mathfrak{m}'_2, \tag{3-56}$$

The probability of detection for the MFSC algorithm can be expressed as

$$P_{\mathrm{d}} = Q\left[\left(\frac{\lambda_{\mathrm{MFSC}} - k\mathfrak{m}'_{2,\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}}}{\sqrt{k\left(\mathfrak{m}'_{4,\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}} - \left(\mathfrak{m}'_{2,\hat{\mathbf{x}}_{\mathbf{s}+\boldsymbol{\eta}}}\right)^2\right)}}\right)\right]. \tag{3-57}$$

Chapter 4

Simulation Results

In this chapter, we show the simulation results of the proposed techniques that compare with the conventional spectrum sensing techniques. For easy to understand, we divide our results into four parts following our proposed methods in chapter 3. Four parts of our simulation include the simulation results of DCAED, the simulation results of FSC, the simulation results of two-stage spectrum sensing, and the simulation results of MFSC.

4.1 The simulation results of DCAED

In this section, we firstly give the performance evaluation of two types of conventional energy detection techniques (CDR and CFAR) and ATED. Then, we compare the performance of these techniques to DCAED. Additive white Gaussian noise (AWGN) channel with SNR between -25 to 0 dB is considered as the communication channel of our simulation. The primary user signal is considered as i.i.d. process. The performance of spectrum sensing techniques are evaluated through 100,000 Monte Carlo simulation. The parameters in the simulation are as follows: N= 1000, P_d=0.9 and P_{fa}=0.01. In addition, noise variance is assumed to be estimated by the secondary user. All the experiments are performed under Windows 8.1 and MATLAB running on a PC equipped with an Intel Core i7 CPU at 3.40 GHz and 32 GB RAM memory.

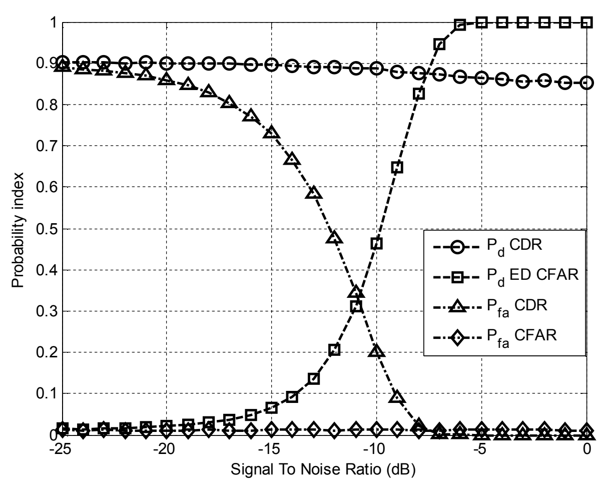


Figure 4-1 Probability of detection and probability of false alarm versus SNR of CDR and CFAR.

Figure 4-1 shows the performance of both P_{fa} and P_d versus SNR of communication channel. The simulation results prove that CDR technique gives high detection performance for all range of SNR. As mentioned in section I, there is always be tradeoff on detection performance (high P_d) by fixing only a single target performance metric. The threshold based on CDR gives high P_{fa} at low SNR. Although the CFAR technique gives low P_{fa} for all range of SNR, it also gives poor detection performance at low SNR levels.

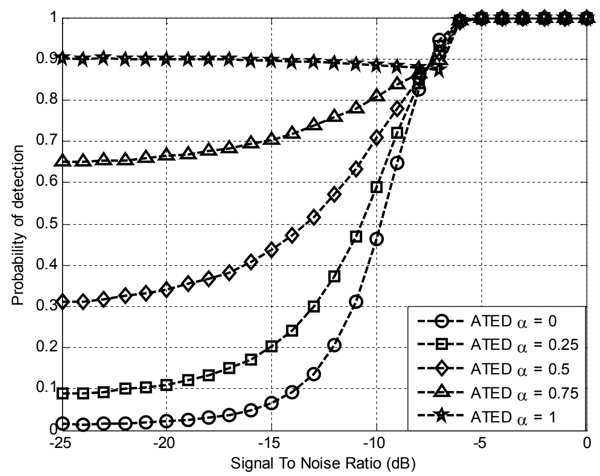


Figure 4-2 Probability of detection versus SNR of ATED.

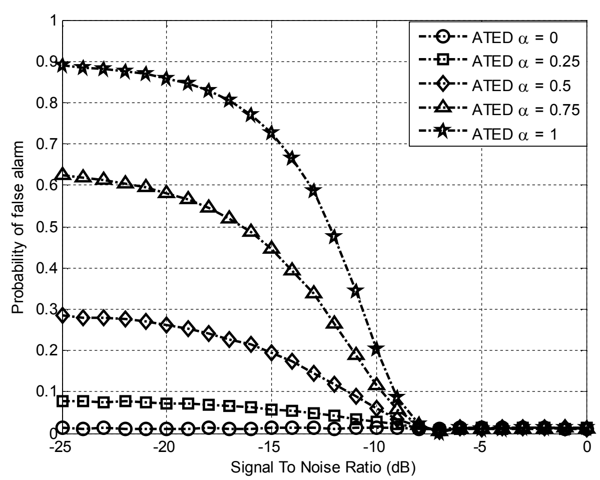


Figure 4-3 Probability of false versus SNR of ATED technique.

Figure 4-2 and Figure 4-3 show the performance of ATED with different in adaptive parameter value in terms of P_d and P_{fa}, respectively. The simulation results show that $\text{ATED}_{\alpha=1}$ gives high probability of detection for all range of SNR as the same as CDR technique. In perspective of probability of false alarm, $\text{ATED}_{\alpha=1}$ gives high P_{fa} at low SNR. On the contrary, $\text{ATED}_{\alpha=0}$ gives low probability of false alarm for all range of SNR as the same as CFAR technique. However, ATED$_{\alpha=0}$ gives low probability of detection at low SNRs. In addition, if we set the value of adaptive parameter between 0 to 1, the performance of ATED is between CFAR and CDR.

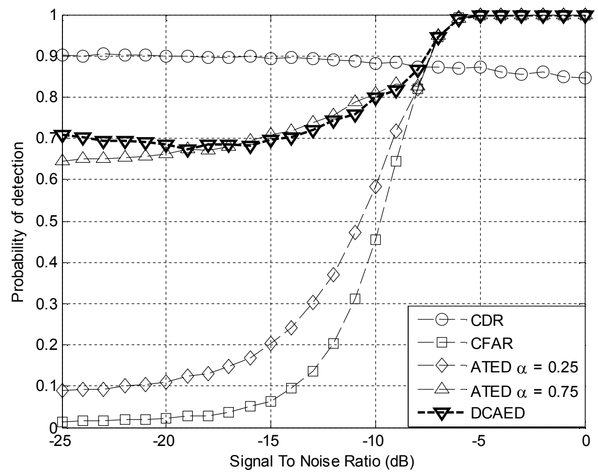


Figure 4-4 Probability of detection of the DCAED as compared to ATED, CDR and CFAR.

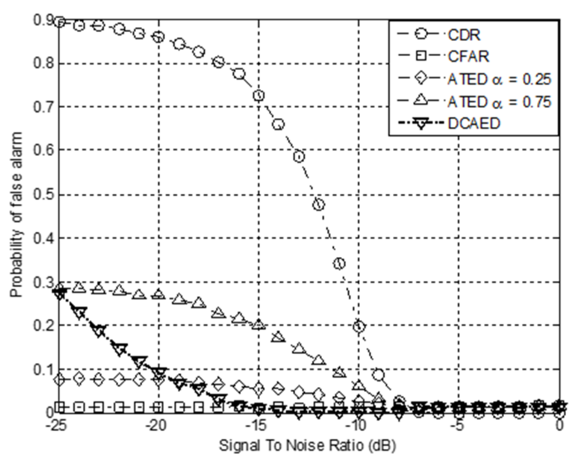


Figure 4-5 Probability of false alarm of the DCAED as compared to ATED, CDR and CFAR

DCAED changes the threshold under different condition of communication channel controlled by the adaptive factor. The adaptive factor is derived from the critical sample of the system which retains the interdepedent between P_{fa} and P_d. Thus, we can conclude that the threshold of DCAED is adapted controlled by P_{fa} and P_d. depending on the condition of icommunication channel. Figure 4-4 compares the probability of detection of the DCAED to ATED$_{\alpha=0.75}$, ATED$_{\alpha=0.25}$, CDR and CFAR. The simulation results show that DCAED gives higher P_d than ATED$_{\alpha=0.75}$, ATED$_{\alpha=0.25}$ and CFAR. On the other hand, the DCAED technique gives higher P_d than CDR techniqe when SNR is higher than-8 dB. As show in Figure 4-5, DCAED gives lower

P_{fa} than ATED$_{\alpha=0.75}$ and CDR. DCAED technique meets the spectrum sensing requirement of IEEE 802.22 when SNR is higer than -20 dB which the spectrum sensing technique has to perform spectrum sensing with probability of false detection less than 0.1.

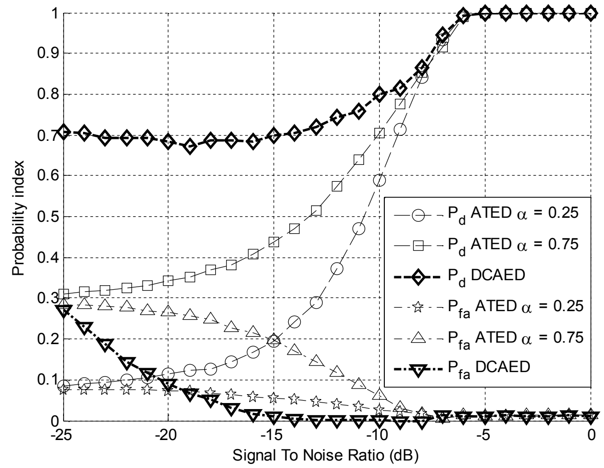


Figure 4-6 Tradeoff in an accuracy of detection of the DCAED as compared to ATED.

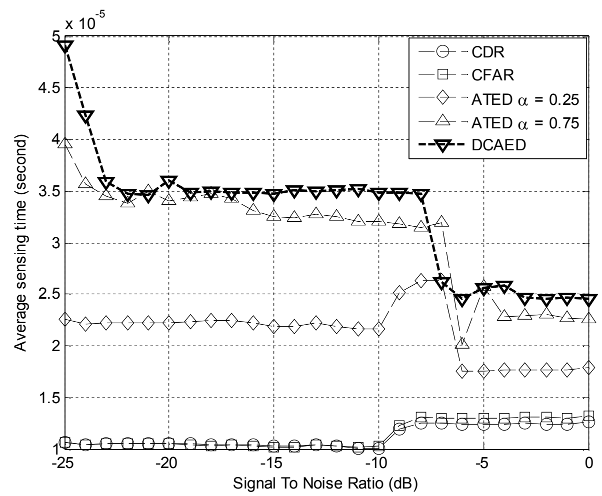


Figure 4-7 Average sensing time of the DCAED as compared to ATED, CDR and CFAR.

Figure 4-6, shows the tradeoff in an accuracy of detection of the DCAED as compared to ATED. The simulation results prove that DCAED overcomes demerits of the tradeoff in the accuracy of detection of ATED. Although DCAED gives higher P_{fa} than ATED$_{\alpha=0.25}$, DCAED gives much higher P_d than ATED$_{\alpha=0.25}$ and ATED$_{\alpha=0.75}$. In addition, the estimated noise variance is used to select the adaptive factor. The adaptive factor under high SNR condition can be computed with less complexity than adaptive factor under low SNR condition. Thus, the DCAED consumes less time in performing spectrum sensing under high SNR condition (as shown in Figure 4-7). The sensing time of DCAED highly achieves the requirement of the IEEE 802.22 standard which is less than 2 seconds. Although the DCAED spends more sensing time than the other technique, the DCAED outperform the tradeoff in an accuracy of detection which is the main disadvantage of the other techniques.

4.2 The simulation results of FSC

4.2.1 Preliminary

In this section, we evaluate the performance of six conventional spectrum sensing techniques — ED, MED, CAV, MME, MFD, and LED — under the assumption that a received WM signal has a randomly occurring pattern. Two important factors — P_{d} and sensing time of each technique — are considered in our performance evaluation.

With an aim to study spectrum sensing performance under different levels of knowledge, the SU is equipped with four different knowledge bases of wireless microphone (WM) signal as described in Table 4-1.

The simulation results of six conventional spectrum sensing techniques — ED, MED, CAV, MME, MFD, and LED — are shown in Table 4-2. As four of the six techniques — ED, MED, CAV, and MME — are blind techniques, their detection performances will not be affected by different knowledge bases. Hence, the individual results of these blind techniques are not shown; rather, they are shown collectively due to the fact that they have similar detection performances. On the other hand, different knowledge bases greatly affect the detection performances of the knowledge-based techniques — MFD and LED. Results on four cases are shown in details.

Table 4-1 Different knowledge bases of PU signal known to an SU.

Case	Description
1	Silent of WM signal is known by SU
2	Soft speaker of WM signal is known by SU
3	Loud speaker of WM signal is known by SU
4	All three patterns of WM signals are known by SU

Figure 4-8 shows the simulation results of MFD and LED for the four cases outlined in Table 4-1. The graph plots P_{d} as a function of SNR. It is clear that the detection performance of MFD is greatly affected by the knowledge base of PU's signal. When SU observes a pattern of WM signal that is not in the knowledge base, the detection performance of MFD greatly degrades.

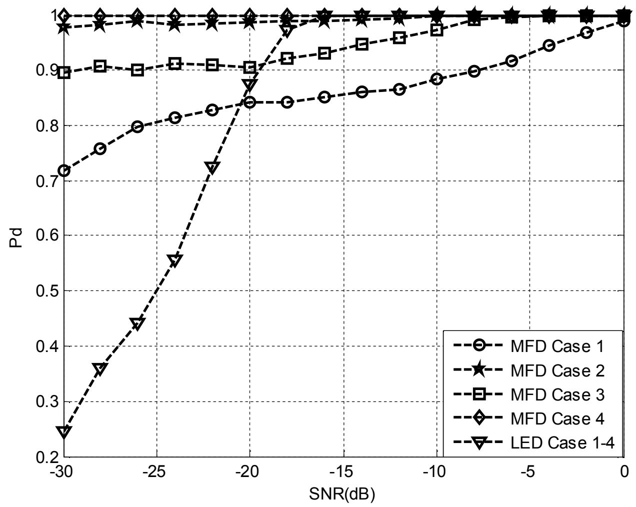


Figure 4-8 Detection performance of MFD and LED under different received wireless microphone signal cases.

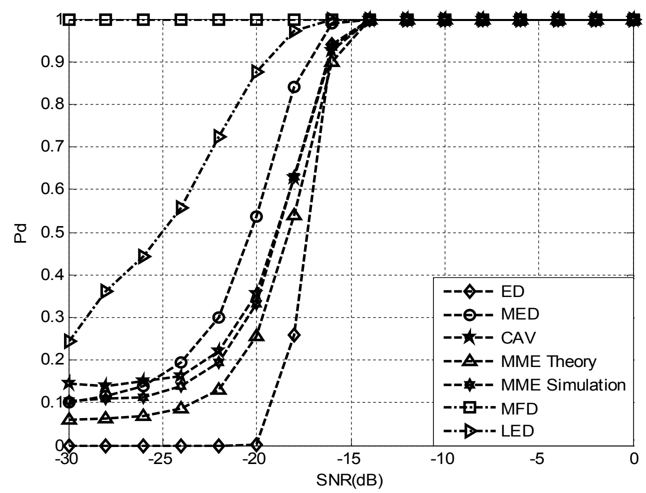


Figure 4-9 Performance comparison of conventional spectrum sensing techniques when the patterns of the PU signal are known.

As depicted in the figure, the detection performance of LED in cases 1–4 is shown using only a single line. This is because the detection performances were practically identical to each other, due to the fact that the leading eigenvectors of the WM signal patterns were similar to each other. Thus, the detection performance of LED was not affected by a difference in WM signal pattern. However, LED inflicts a high computational burden upon the SU when performing spectrum sensing; thus, the associated sensing time is often substantial.

Figure 4-9 shows the performance comparison of conventional spectrum sensing techniques when the patterns of WM signals are known. MFD offers the best detection performance among the spectrum sensing techniques. When evaluating the performance of MME, the calculated MME threshold (theoretical), γ_{MME}, offer an implausible performance at low SNRs.

In [54], the authors improve the detection performance of MME by finding new thresholds through Monte Carlo simulations. To compare the performance of MME under the different types of thresholds (theoretical and Monte Carlo simulations), we present the performance of "MME Theory" and "MME Simulation" in Figure 4-9. Note that "MME Theory" denotes experimental results where the threshold is calculated from a theoretical formula. "MME Simulation" denotes experimental results where the threshold is estimated through Monte Carlo simulations.

Table 4-2 gives a performance comparison of conventional spectrum sensing techniques for various cases of prior knowledge. The SNR required of a spectrum sensing technique to meet the required accuracy of detection (that is, $P_{\mathrm{d}} \geq 0.9$) [43], is given in the "Critical SNR" column of Table 4-2. The lower the "Critical SNR" value, the more tolerant to noise the technique is. From Table 4-2, the knowledge-based spectrum sensing techniques — MFD and LED— are confirmed to be more tolerant to noise than the blind techniques.

On the other hand, the average sensing time shown for each technique is based on the average from the Monte Carlo simulations. As shown in Table 4-2, ED consumes the least average sensing time, whereas LED consumes the longest average sensing time. These average sensing time values are used as a benchmark when evaluating the average sensing time of the FSC algorithm.

Moreover, the results in Table 4-2 show that ED offers the maximum number of channels per sensing period. However, there is no standard or requirement that defines the minimum number of channels that should be monitored in a given sensing period. If the number of channels per sensing period increases, then the SU will have more opportunities to utilize the unused licensed band.

Table 4-2 Performance comparison of conventional spectrum sensing techniques.

Sensing technique			**Prior knowledge**			**Ability to detect wireless microphone signal**		
			Waveform pattern	Noise power	Memory (Kbytes)	Critical SNR ($P_{\mathrm{d}} \geq 0.9$)	Average sensing time (ms)	Channels/Sensing period of 2 seconds
Blind spectrum sensing	ED		✗	✓	0	-16 dB	0.04997	3,602
	MED		✗	✓	0	-16 dB	2.6	69
	CAV		✗	✗	0	-16 dB	2.5	72
	MME		✗	✗	0	-16 dB	2.9	62
Spectrum sensing based on prior knowledge	MFD	Case 1	✓	✓	40	-8 dB	2.5	72
		Case 2	✓	✓	40	-30 dB	2.5	72
		Case 3	✓	✓	40	-30 dB	2.5	72
		Case 4	✓	✓	120	-30 dB	5.4	33
	LED	Case 1	✓	✓	0.192	-18 dB	78.09	2
		Case 2	✓	✓	0.064	-18 dB	78.09	2
		Case 3	✓	✓	0.064	-18 dB	78.09	2
		Case 4	✓	✓	0.192	-18 dB	80.7	2

4.1.2 Simulation Results

In this section, we give the simulation results of eight spectrum sensing techniques. The transmitted PU signals are assumed to be WM signals, based on IEEE 802.22, whereby the patterns of the WM signals are assumed to be in the knowledge base of the SU. The parameters of the WM signals are shown in Table 4-1. A single received WM signal is assumed to contain one of three randomly occurring patterns. The communication channel between the transmitter and the receiver is assumed to be an AWGN channel, and the SNR at the receiver is assumed to be between -30 dB and 0 dB. The other parameters that were used in the simulations took the following values: n= 5,000; L= 10; and P_{fa} = 0.1. All the experiments are performed under Windows 7 and MATLAB running on a PC equipped with an Intel Dual-Core CPU at 2.93 GHz and 4 GB RAM memory.

As depicted in Figure 4-10, the FSC algorithm gives a better detection performance than other conventional spectrum sensing techniques, except MFD, which is known as the optimum spectrum sensing technique. The critical SNR of the FSC algorithm is -24 dB (see Table 4-3). From the perspective of sensing time, the FSC algorithm consumes less sensing time than the other conventional techniques, except ED (see Table 4-3). The reason for this is that the FSC algorithm performs spectrum sensing with little computational burden due to the small size of the weight vector ($\hat{\mathbf{x}}$). Calculated from the averaged sensing time of FSC, the FSC algorithm can sense 3,370 channels per sensing period. When compared with the results in Table 4-2, we can see that the FSC algorithm can perform spectrum sensing with a number of communication channels that rivals that of ED.

To validate the performance of the FSC algorithm, graphs of $P_{\mathrm{d(FSC)}}$, $P_{\mathrm{m(FSC)}}$, and $P_{\mathrm{fa(FSC)}}$ are shown in Figure 4-11(a). In this figure, as SNR increases, $P_{\mathrm{d(FSC)}}$ increases while $P_{\mathrm{m(FSC)}}$ and $P_{\mathrm{fa(FSC)}}$ decrease. The simulation results are as we expected, and this is explained as follows. By projecting the received signal to the proposed coordinate system, we obtained the weight vector and weight of correspondence between the received signal and the coordinate system. We found that the weight vector effectively represents the WM signal especially when SNR is higher than -18 dB. When SNR is lower than -18 dB, where noise power is much greater than the WM signal power, the weight vector is contaminated with noise. Hence, the magnitude of the weight of correspondence between the received signal and the coordinate system is lower than the predetermined FSC threshold, which causes misdetection.

However, $P_{\mathrm{d(FSC)}}$ is still higher than the P_{d}s of other conventional techniques, including ED, MED, CAV, MME, and LED. This is because the effect of the noise on the weight vector is less than that on the WM signal.

To evaluate the tradeoff between $P_{\mathrm{m(FSC)}}$ and $P_{\mathrm{fa(FSC)}}$, $P_{\mathrm{m(FSC)}}$ is plotted as a function of $P_{\mathrm{fa(FSC)}}$, as shown in Figure 4-11(b). It should be noted that $P_{\mathrm{m(FSC)}}$ is greater than 0 when the SNR is lower than -18 dB; hence, $P_{\mathrm{m(FSC)}}$ at three different SNRs — -20 dB, -26 dB, and -30 dB — is shown. From Figure 4-11(b), it can be seen that $P_{\mathrm{m(FSC)}}$ slightly decreases when $P_{\mathrm{fa(FSC)}}$ increases, which is similar to what happens in the cases of the other conventional techniques.

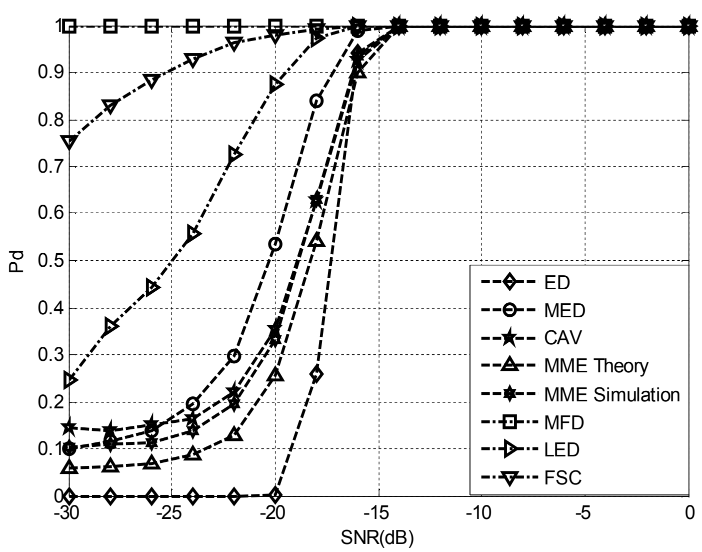
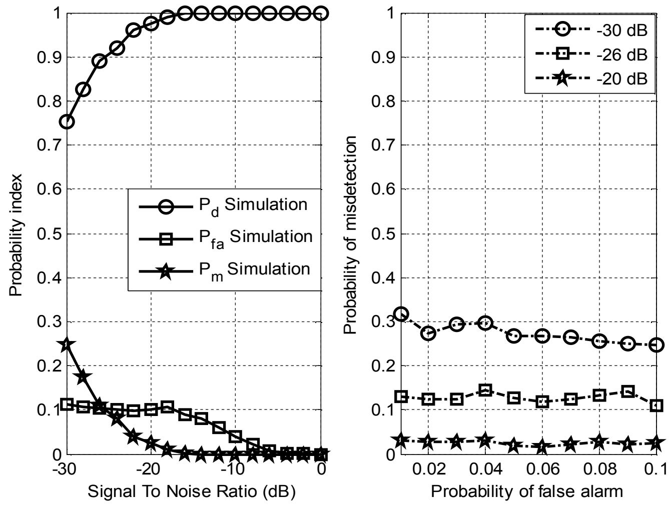


Figure 4-10 Probability of detection vs. SNRs of ED, MED, CAV, MME, MFD, LED, and FSC.



(a) (b)

Figure 4-11 Performance of FSC algorithm.

Table 4-3 Comparison of critical SNR and average sensing time (case 4).

Sensing technique		Critical SNR ($P_{\mathrm{d}} \geq 0.9$)	Average sensing time (ms)
Blind spectrum sensing	ED	-16 dB	0.0499
	MED	-16 dB	2.6
	CAV	-16 dB	2.5
	MME	-16 dB	2.9
Spectrum sensing based on prior knowledge	MFD	-30 dB	5.4
	LED	-18 dB	30.7
	FSC	-24 dB	0.0534

To evaluate the overall performances of the spectrum sensing techniques, we combine two performance metrics, P_{d} and average sensing time of each technique, using a standard multi-criteria ranking technique — analytic hierarchy process (AHP) [30]. In the first step, we have to determine the importance ratio between P_{d} and average sensing time, which has never been standardized. Herein, the importance ratios are set as follows: 1:7, 1:5, 1:3, 1:2, 1:1, 2:1, 3:1, 5:1, and 7:1. It should be noted that the importance ratio of 1:7 means that the P_{d} is 7 times more important than the average sensing time, while 7:1 means the P_{d} is 7 times less important than the average sensing time. As shown in Figure 4-12, the FSC algorithm gives the highest overall performance at any weight of importance. The reason is that the FSC algorithm gives a high rate of detection while utilizing a short sensing time.

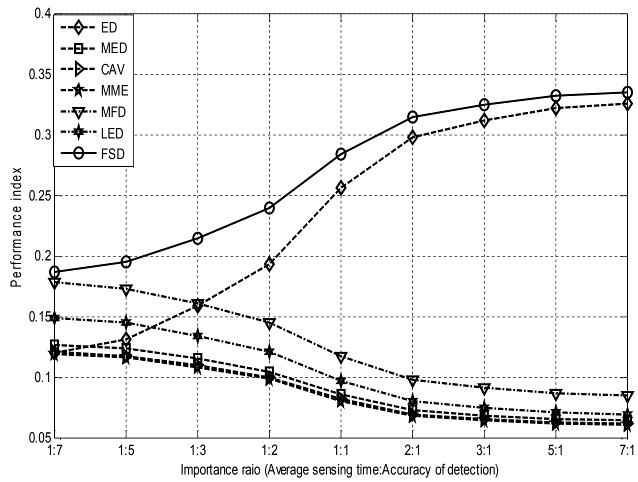


Figure 4-12 Performance comparison using AHP algorithm.

4.3 The simulation of two-stage spectrum sensing

In our proposed schemes, there are 2 main parameters that have to be considered, including $\mathrm{P_{fa}}$ and L. Threshold of the proposed techniques can be found by using (2-21), (2-28) and (3-45). Since these parameters relate to each other and also affect to the performace of the proposed techniques, these parameters need to change simultaneously. Figure 4-13 and Figure 4-14 show the probability of detection and the average sensing time as a function of SNR with difference in smoothing factors when noise power uncertainty occurs (β = 2 dB) and $\mathrm{P_{fa}}$=0.1, respectively. As shown in the figures, two-stage spectrum sensing techniques offer more reliable detection under noise power uncertainty factor equal to 1 when the smoothing factor increaes. However, an increase in the smoothing factor causes these techniques consume more time in performing spectrum sensing.

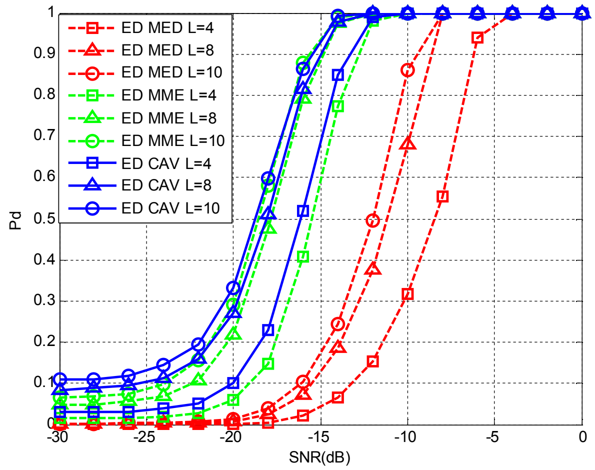


Figure 4-13 Probability of detection versus SNR of two-stage spectrum sensing techniques with difference in smooting factors (L)
when the uncertainty of noise power occur (β =2 dB) and P_{fa}=0.1.

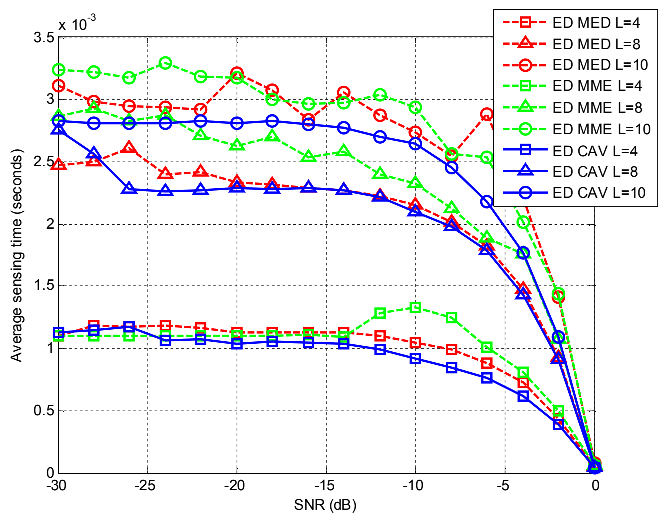


Figure 4-14 Average sensing time versus SNR of two-stage spectrum sensing techniques with difference in smooting factors (L)
when the uncertainty of noise power occur (β =2 dB) and P_{fa}=0.1.

Figure 4-15 and Figure 4-16 show the probability of detection and the average sensing time as a function of SNR with difference in smoothing factors when noise power uncertainty occurs (β = 2 dB) and P_{fa}=0.2, respectively. As mentioned earlier, an increase in smoothing factor makes these techniques more time consuming in performing spectrum sensing. By comparing Figure 4-13 and Figure 4-15, two-stage spectrum sensing techniques offer more reliable detection when the smoothing factor is eqaul to 10 and P_{fa}=0.2. Although the smoothing factor equal to 10 makes two-stage spectrum sensing techniques more time consuming in performing spectrum sensing, the primary user can ensure that it is protected from harmful interference caused by the secondary user.

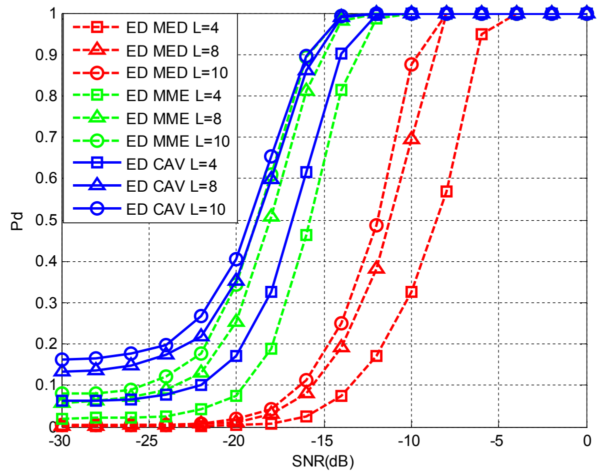


Figure 4-15 Probability of detection versus SNR of two-stage spectrum sensing techniques with difference in smooting factors (L)

when the uncertainty of noise power occur (β =2 dB) and P_{fa}=0.2.

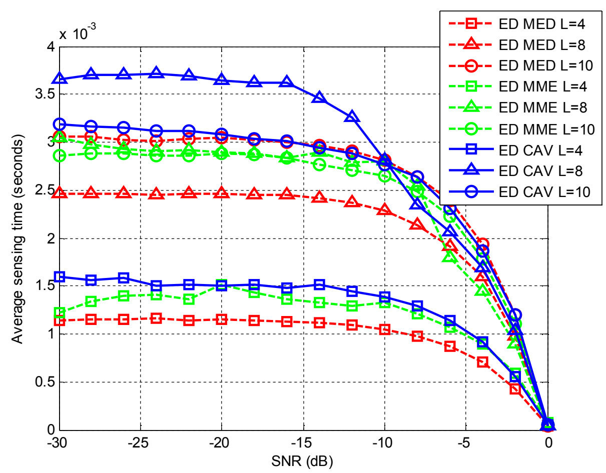


Figure 4-16 Average sensing time versus SNR of two-stage spectrum sensing techniques with difference in smooting factors (L)

when the uncertainty of noise power occur (β =2 dB) and P_{fa}=0.2.

Figure 4-17 and Figure 4-18 show the probability as a function of SNR when noise power uncertainty factor (β) equal to 1 and 2 dB, respectively. Figure 4-19 and Figure 4-20 show the average sensing time as a function of SNR when noise power uncertainty factor (β) equal to 1 and 2 dB, respectively. Simulation results proved that the proposed of ED to CAV two-stage spectrum sensing technique offers detection performance nearly to CAV technique. However, at high SNRs environment, the proposed of ED to CAV two-stage spectrum sensing technique uses less sensing time than CAV. From the simulation results, the proposed of ED to CAV two-stage spectrum sensing technique offers an accurate performance when smoothing factor L=10 and P_{fa}=0.2. Even though the proposed technique takes the longest time in the sensing period, it offers much more reliable detection than the others. It is worth using this period of time to protect the primary user from harmful interference caused by the secondary user.

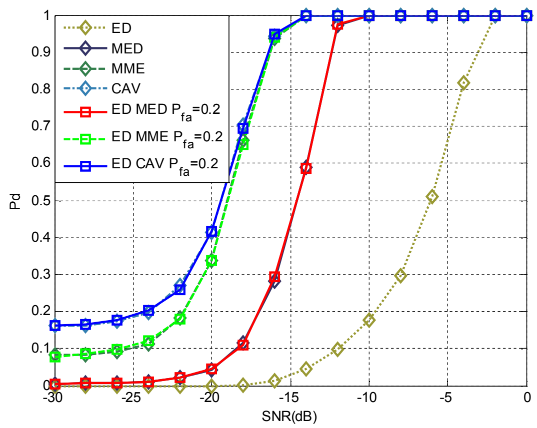


Figure 4-17 Probability of detection versus SNR when the uncertainty of noise power occur (β =1 dB).

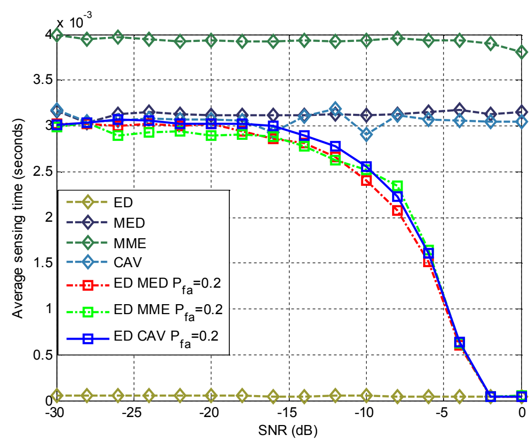


Figure 4-18 Average sensing time versus SNR when the uncertainty of noise power occur (β =1 dB).

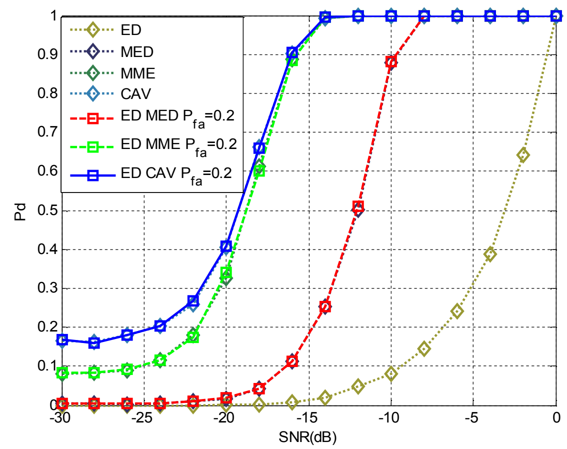


Figure 4-19 Probability of detection versus SNR
when the uncertainty of noise power occur (β =2 dB).

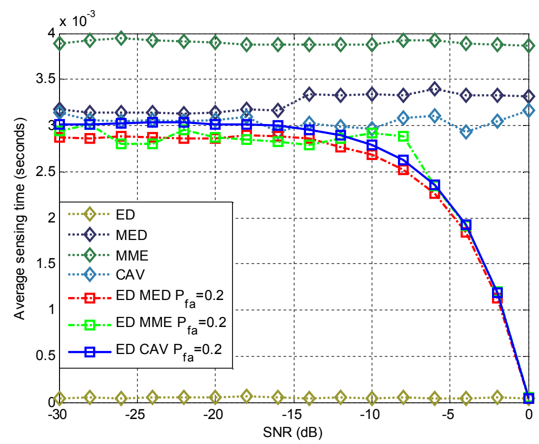


Figure 4-20 Average sensing time versus SNR
when the uncertainty of noise power occur (β =2 dB).

4.4 The simulation results of MFSC

In this section, we give the performance comparison of MFD, LED, MFSC algorithm for additive white Gaussian noise (AWGN) channel under noise uncertainty and path loss effect when a random occurring pattern of WM signal is considered as the PU signal. The distance (d) between WM device and the SU is set within the range of 10 to 1000 meters. The loss constant (C) is set be 0.00031623, then the received signal power is -95 dBm at 100 m [43]. The noise uncertainty factor (B) is between 0 to 2 dB [75]. It should be noticed that when B is 0 means that the noise uncertainty does not occur. Other parameters are setting as follows: $N = 5000$, $\aleph = 2$, $P_{\mathrm{d}} = 0.9$ and $P_{\mathrm{fa}} = 0.01$. All the experiments are done by using MATLAB and averaged on 10,000 Monte-Carlo realizations.

As shown in Figure 4-21, MFD gives the highest P_{d} among these techniques. In perspective of P_{d}, MFD meets the spectrum sensing requirement, which P_{d} should greater than or equal to 0.9, when *d* is less than 650 m. However, P_{fa} of MFD does not meet the requirement, which P_{fa} should less than 0.1, at any distance. This means that the PU is greatly protected from interference caused by SU. However, the SU has a high probability to lose the opportunities to utilize the available spectrum band. On the other hand, MFSC algorithm meets the requirement in perspective of P_{d} with shorter distance. Nevertheless, MFSC meets the requirement in perspective of P_{fa} for all distances. For LED, it gives the worst detection performance when compared to the others. As shown in Figure. 4-22, MFSC algorithm consumes much less sensing time than the others. During the evaluation, we also correct the space of database requirement of these techniques. We found that LED requires much less space of database when it consumes only 0.197 Kbytes while MFD and MFSC require 120 and 80 Kbytes, respectively.

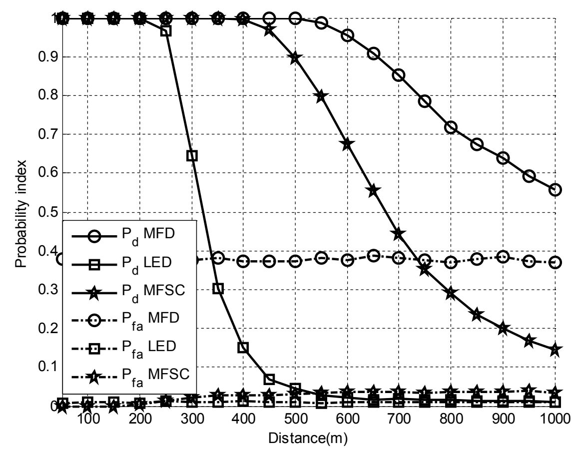


Figure 4-21. Performance comparison of MFD, LED and MFSC when B is 0.

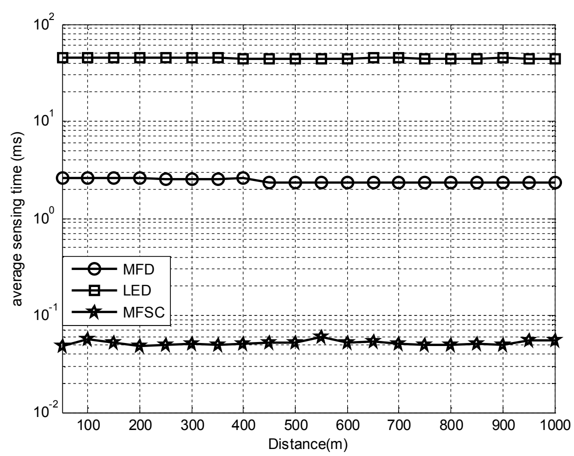


Figure 4-22 Average sensing time of MFD, LED and MFSC when B is 0.

Figure 4-23 compares the detection performance when B is 1. As a results, MFD still gives the highest P_{d}. However, P_{fa} is now less than 0.1. This is because there is an uncertain in noise power which the power may less than the estimated noise power. It means that the effect of noise is lower and then it is easy to distinguish between PU signal and noise. On the other hand, the performance LED and MFSC algorithm, which perform spectrum sensing under framework of PCA algorithm, are nearly the same as when noise uncertainty does not occur. In perspective of average sensing time (as shown in Figure. 4-24), MFSC algorithm still consumes the least average sensing time.

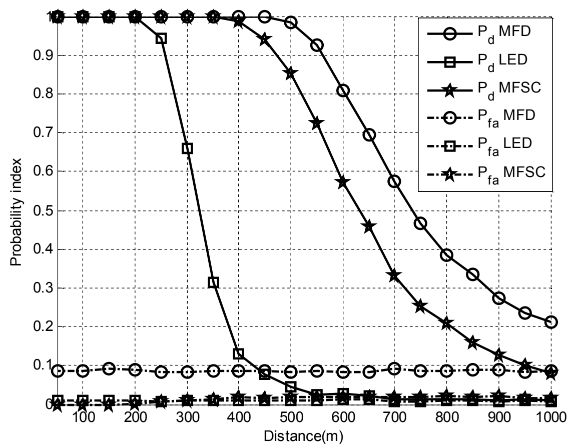


Figure 4-23 Performance comparison of MFD, LED and MFSC when B is 1.

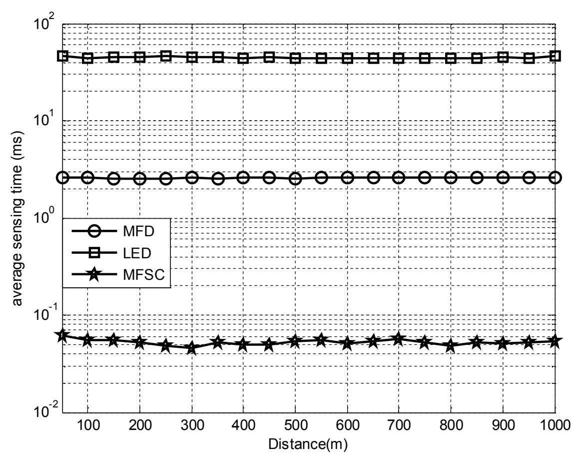


Figure 4-24 Average sensing time of MFD, LED and MFSC when B is 1.

As shown in Figure 4-25, the detection performance of MFSC algorithm is now nearly to MFD because the occurrence of noise uncertainty greatly degrades the detection performance of MFD but does not degrade the detection performance of MFSC algorithm. MFSC algorithm gives higher P_{d} than MFD when the distance is greater than 600 m. This means that when the strength of PU signal is attenuated by path loss together with the increasing in an effect of noise uncertainty, matched filter lose its ability to measure the similarity between received signal and a known PU signal, which is kept in the database, and cannot distinguish them. For LED, it gives the worst detection performance among these techniques. However, we can noticed that LED is the most robustness techniques to the occurrence of noise uncertainty because it gives the same P_{d} even the strength of noise uncertainty increases. As shown in Figure 4-26, the average sensing time of these techniques are the same as when B is 0 or 1.

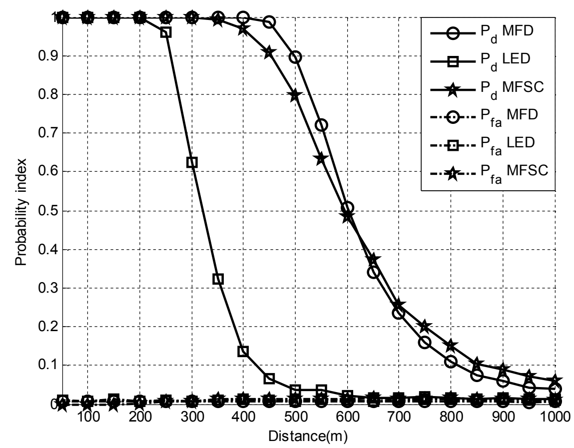


Figure 4-25 Performance comparison of MFD, LED and MFSC when B is 2.

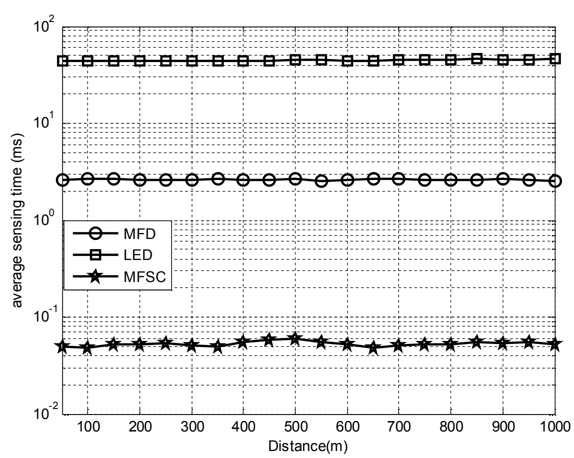


Figure 4-26 Average sensing time of MFD, LED and MFSC when B is 2

From the simulation results, MFD offers the best detection performance in perspective of P_{d}. However, MFD does not meet the spectrum sensing requirement in perspective of P_{fa} at any distance when noise uncertainty does not occur. Moreover, the occurrence of noise uncertainty greatly degrades the detection performance of MFD. On the other hand, MFSC algorithm gives better detection performance than LED but worse than MFD. MFSC algorithm is more robust to the occurrence of noise uncertainty than MFD. In addition, MFSC algorithm gives higher P_{d} than MFD when the distance is greater than 600 m together with 2 dB of noise uncertainty factor (B). In perspective of average sensing time, MFSC algorithm consumes the least average sensing time for all noise uncertainty factors (B) and distances. For LED, it is the most robustness techniques to the occurrence of noise uncertainty and requires much less space database than the others.

Chapter 5

Conclusion

This project proposes the novel spectrum sensing techniques in CR network for SG communication. The proposed techniques have a minimum time requirement and give a better performance than the conventional spectrum sensing methods. Moreover, we consider two channel environments including AWGN channel and the channel that consider the noise uncertainty and path loss effect.

Firstly, we propose “double constraints adaptive energy detection (DCAED)” for spectrum sensing in cognitive radio network. DCAED changes the system threshold depending on the condition of communication channel. Different from other adaptive ED and conventional ED, DCAED exploits the interdependent between probability of detection and probability of false alarm through the critical sample to set a new threshold. Thus, we can conclude that the decision threshold of DCAED is controlled by 2 target accuracy of detection performance metrics. The simulation results show that DCAED gives an accuracy detection performance even at low SNR condition while it also highly achieve the requirements of IEEE 802.22 standard in perspective of sensing time. DCAED can be well implemented when the noise variance can be estimated by the secondary user. Moreover, DCAED appropriates to real-time application in practical cognitive radio network because it does need any prior knowledge about signal pattern of primary user and consumes short sensing time.

Secondly, we propose fast spectrum sensing with coordinate system (FSC). The FSC extracts only two significant features of the WM signals to build a new coordinate system as the SU’s knowledge base. The FSC algorithm determines the existence of a PU by comparing the FSC decision statistic to the FSC threshold. Using our new coordinate system, the FSC requires less space for SU’s knowledge base compared to that of other knowledge-based techniques. By measuring the magnitude of the weight of correspondence between the received signal and the coordinate system, FSC performs spectrum sensing with little computational burden and utilizes a short sensing time, while offering a detection accuracy close to that of MFD. The FSC can be well implemented by an SU, when the patterns of the PU signal are known to the SU, with much less computational complexity and sensing time than any of the other knowledge-based spectrum sensing techniques considered in this paper. Moreover, FSC is appropriate for real-time application because it uses a sensing time that is as short as that of ED.

Thirdly, we propose two novel schemes of two-stage spectrum sensing technique for CR. The proposed schemes are ED to CAV two stage spectrum sensing and ED to MME two stage spectrum sensing. The received signal is first monitored by the first stage such as ED. The first stage gives reliable detection at high SNRs environment. By exploiting CAV and MME technique as a second stage, our proposed algorithms give better detection performance than the existing two stage spectrum sensing techniques. The proposed schemes offer an accurate detection when the uncertainty of noise power occurs and use short sensing time at high SNRs environment. Even though the proposed techniques take the longest time in the sensing period among two-stage spectrum sensing techniques, they offer much more reliable detection than the others.

Finally, we introduce a modified- fast spectrum sensing with coordinate system (MFSC) which is re-derive some parameters form conventional fast spectrum sensing with coordinate system (FSC) in order to perform spectrum sensing under noise uncertainty together with path loss effect. Then the detection performance of three knowledge-based spectrum sensing techniques — MFD, LED and MFSC — are evaluated under these factors. From the simulation results, MFD gives the best detection performance among these techniques however its detection performance greatly degrades due to the occurrence of noise uncertainty. LED is the most robustness to the occurrence of noise uncertainty and also consumes the least space of database. MFSC algorithm is the most achievable of spectrum sensing requirement when it give high detection performance while consumes the least average sensing time under noise uncertainty.

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